Trois essais sur le risque systémique

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Three Essays on Systemic Risk

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Introduction

Systemic risk, defined in a broad sense as the risk of a global financial meltdown, has long been a subject of research in finance, both in economics and management. The classical example is the banking crisis and the Great Depression of the 1930s (see de Bandt and Hartmann, 2002, for a survey of major works on systemic risk at the time). But it is undoubtedly the 2007-08 financial crisis that has led to deeply renewing the interest of regulators and researchers in the concept of systemic risk, especially regarding the forthcoming macroprudential regulation.

This dissertation is part of the debate on systemic risk and banking supervision by displaying three main purposes which are: (*i*) to evaluate the major systemic risk measures, (*ii*) to apply and evaluate them from a regulator point of view, and (*iii*) to suggest new techniques to improve these measures or to propose new measures. Indeed, even if the concept of systemic risk is well-known, its measurement remains a challenge (see Bisias et al., 2012, for a definition and a survey of systemic risk measures). By definition, systemic risk is unobservable and only systemic events can be observed.[1] However, from a regulatory perspective, it is obvious that the risk of a system-wide collapse should be measured and expressed in a probabilistic environment. More specifically, setting a macroprudential regulation requires the evaluation of the contribution of each financial institution to systemic risk as an externality. How can the contribution of a financial institution to the system-wide risk be evaluated? How can such a measure such a measure be validated? These issues and the dramatic consequences on the global economy of the bankruptcy of Lehman Brothers in 2008 have led to a profound questioning about the prudential regulations (so far mainly focused on the microprudential aspect in which the stability of each financial institution ensures the system-wide stability) as well as the academic notion of systemic risk (Hansen, 2014).

From an academic point of view, systemic risk is often related to the concept of contagion. To experience a systemic event, a trigger point is needed. According to the European Central Bank (ECB, 2009), this trigger point can come from two sources: an exogenous shock, i.e. an idiosyncratic event such as the failure of a market or a financial institution, or an endogenous shock within the financial system, i.e. a global

[1] To be more precise, we should mention the concept of systemic uncertainty (in the sense of Knight), since it is assumed that systemic events can be probabilized.

macroeconomic imbalance.[2] These adverse effects are spread through the entire financial system due to spillover effects which are local, and/or contagion effects which are global. Finally, a substantial part of the real economy is affected, leading to a lower economic welfare. Thus, the systemic threat refers to the idea of negative externalities. The risk-taking behavior of a financial institution may impact not only its shareholders and managers, but also other financial institutions (Lepetit, 2010). This interconnectedness arises from financial transactions in the interbank market (Rochet and Tirole, 1996), or asset commonality among banks (Allen, Babus and Carletti, 2012).

The general idea of a macroprudential regulation is based on the fact that a financial institution has to internalize its negative externalities.[3] This paradigm shift on the regulatory framework has been commissioned by a strong international political willpower, as illustrated by the six meetings of the G-20 heads of governments about financial markets and the world economy that took place from 2008 to 2011. This guideline has produced significant updates to financial regulation that were materialized in 2010 by the Dodd-Frank Wall Street Reform and Consumer Protection Act in the United States, and by the third Basel Accord signed by the members of the Basel Committee on Banking Supervision (BCBS).[4]

Hence, if the consumers' protection against the risk of failure of their bank was at the heart of the microprudential banking regulations, the financial crisis of 2008 has prompted to take into account the protection of the whole financial market against a systemic crisis (Rochet, 2008). To limit the risk of failure of a given institution, the banks under the Basel II regulation have to satisfy to capital adequacy requirement set for market, counterparty and operational risks. Most of the time, these capital amounts are computed thanks to banks' internal risk models. The transition to a macroprudential regulation (Basel III for example) involves the identification of the major financial institutions that contribute most to the overall risk of the financial system – the so-called Systemically Important Financial Institutions (SIFIs). As SIFIs pose a major threat to the system, they have to be subject to tighter supervision, extra capital requirements, and liquidity buffers (Financial Stability Board, 2011a). These additional capital requirements should be proportionate to the contribution of each financial institution to the system-wide risk.

Three crucial questions arise in this context: (*i*) how to identify Systemically Important Financial Institutions (SIFIs), (*ii*) how to measure the systemic risk contribution in order to set the capital surcharge, and (*iii*) how to reveal banks' commonalities in trading in order to prevent systemic events.

[2] See de Bandt, Hartmann and Peydró (2012) for a clear distinction between a systemic event in the "narrow" and "broad" senses, as well as its classification into "strong" or "weak". Their updated survey on systemic risk focuses on contagion effects which are the consequence of a strong systemic event in the narrow sense.

[3] Whatever the source of its externalities, market risk, credit risk, liquidity risk or operational risk.

[4] The United States are members of the BCBS.

Identifying Systemically Important Financial Institutions

In some aspects, banking and biology have many similarities since they are both complex systems. This is probably why the contagion analogy between the spread of financial shocks and the transmission of infectious diseases has been so often used in the academic literature (Haldane and May, 2011). Banks are connected to each other (through their cross-asset and liability positions and their exposures to common risk factors) which means that they suffer from but also contribute to the spread of financial shocks. In case of pandemic the patient zero is looked for in order to figure out the cause of the infection; in case of a systemic event, it is the financial institutions whose characteristics (size, interconnectedness, specific role in the markets, etc.) and activity generate the greatest threat to the stability of the financial system as a whole, i.e. SIFIs or Global Systemically Important Financial Institutions (G-SIFIs), which are looked for.

How to identify systemically important financial institutions? To assess the systemic importance of G-SIFIs, an indicator-based measurement approach has been developed by the regulators. The framework proposed by the BCBS (Financial Stability Board - International Monetary Fund - Bank for International Settlements, 2009; FSB, 2011b; Financial Stability Oversight Council, 2012a) provides a score based on five systemic risk factors: size, interconnectedness, global (cross-jurisdictional) activity, substitutability/financial institution infrastructure, and complexity. The first three follow the recommendation of the FSB-IMF-BIS report of 2009, whereas the last two have been added by the BCBS itself, since complex and international SIFIs are more costly and longer to disentangle (BCBS, 2011a). In this approach based on scores, the fundamental question that arises, beyond the choice of the indicators that should be included in the score, is their relative weight. The BCBS has chosen an equally weighted score in which each factor has a total weight of 20% in the score construction. On the same principle, an equal weight is also assigned to all indicators used in the composition of a factor. These indicators are well-defined and correspond to precise accounting or market values (a detailed list of these individual indicators is provided by the BCBS, 2013b).

The individual score of a given financial institution is then used twice. First, the score is compared to a cutoff level, set by the BCBS given their supervisory judgment. Each financial institution with a score above this threshold is considered as a G-SIFI and is submitted to tighter supervision. Second, scores are used to set the regulatory capital surcharge. Thus, the next step is to introduce the G-SIFIs' scores in a bucketing approach which allocates G-SIFIs into four buckets with their own systemic importance. Inside a bucket, the systemic importance of these G-SIFIs is homogeneous. Finally, the magnitude of the higher loss absorbency (HLA) requirement applied to cover the individual contribution to systemic risk varies according to the bucket where the G-SIFI is put. This higher level of capital, expressed as a percentage of the risk-weighted assets, goes from 1% to 2.5%, corresponding to an increase of 0.5% per bucket. Since 2012, the list of G-SIFIs is disclosed once a year.

This regulatory framework becomes a kind of benchmark for the identification of SIFIs (Weistroffer, 2011) even if this indicator-based approach aggregates multiple indicators, including private data. However, this methodology raises a large number of issues. First, Hurlin and Pérignon (2013) show that an equally weighted score can lead to overstate the importance of the most volatile indicators. Second, beyond the methodology, publish a list of SIFIs may have unintended consequences. Like the investors' perception of the too-big-to-fail theory, a too-systemic-to-fail view could also lead to positive valuation effects. Indeed, the market capitalization of such a financial institution may growth whatever its risk management efforts to reduce its contribution to systemic risk. In other words, banks may have an incentive to appear as a SIFIs even if it induces a surcharge of capital and a tighter monitoring from regulators. Moenninghoff, Ongena and Wieandt (2014) have contributed to this debate in a recent empirical study where they observe that the new regulation negatively affects the value of the newly regulated financial institutions, yet they highlight that the official designation of G-SIFIs has partly offset the desired impact. Third, only banks are taken into account within this framework. Nevertheless, the financial system is composed of heterogeneous agents, such as insurance companies (van Lelyveld, Liedorp and Kampman, 2009) and global hedge funds (Chan et al., 2006, attempt to quantify their potential impact on systemic risk), and both may be systemically important under certain circumstances. The collapse of Long Term Capital Management in 1998 shed light on the involvement of hedge funds in systemic risk.

Another issue with this approach lies in defining the scope of the financial system of reference (see Zigrand, 2014, for a definition of what "system" means in the notion of systemic risk). Have a European regulator to assess the risk of externalities generated by the activities of European banks on the Asian and American banks, or should be restricted to the analysis of impacts in the European financial system? More generally, this question about the appropriate level-playing field is part of the identification of G-SIFIs and Domestically Systemically Important Financial Institutions (D-SIFIs). This identification of D-SIFIs is paramount when a regulator wants to analyze the impact of a potential failure on a national or regional financial system. Thus, the topology of the system is important and we have to investigate and delimitate the area in which a financial institution has a potential impact in case of distress. For example, in August 2014, the Portuguese bank Banco Espirito Santos has been recapitalized with a state aid of 4.4 billion euros due to large exposures. This bank has never been identified as a G-SIFI in spite of its poor results in the 2011 stress tests. This institution may be only a D-SIFI since no European crisis has followed this bail-in. To address this domestic systemic risk, BCBS (2012) proposes a set of twelve principles to identify D-SIFIs and assess their accurate magnitude of HLA. Unfortunately, this framework is not operational yet and a disaster, such as the one of August 2014 could happen again with potentially damaging consequences in Europe. Indeed, the identification of such a D-SIFI is a high priority for regulators but also for academic researchers (Brämer and Gischer, 2011; Engle, Jondeau and Rockinger, 2014). My PhD thesis contributes to this literature by proposing a way to establish the financial institutions which may be systemically risky at a nation level.

The methodology proposed by regulators is not the only way to point out systemically risky financial institutions. Researchers have proposed several measures to assess the systemic importance of a financial institution. Their main difficulty is that they usually do not have access to a set of data able to measure the interconnectedness in banks' balance sheets (Cerutti, Claessens and McGuire, 2014). Therefore, systemic risk measures developped by researchers are mainly based on market data and on publicly available balance-sheet data.

Systemic Risk Measurement

As shown by the regulatory approach, systemic risk cannot be defined according to a single criterion. Zhou (2009) emphasizes this point when he studies the relation between the size of a financial institution and its systemic importance. His conclusion is that size is not a proxy of systemic risk. Additional characteristics have to be considered, relying on all the components making a financial institution systemically risky. Bisias et al. (2012) survey thirty-one measures of systemic risk in the economic and financial literature from the granular foundations and network measures to the forward-looking risk measurement, among others. De Bandt et al. (2013) also survey a large number of quantitative indicators, particularly institution-level measures. This former set of measures is well designed to identify SIFIs.

In order to gauge the contribution of a given institution to the overall systemic risk, two ways can be distinguished. On the one hand, measures based on market data, such as stock returns or Credit Default Swaps (CDS) data, and on the other hand measures based on balance-sheet and regulatory data (when they are available), such as bilateral exposures.

The first subset of measures focuses on market data. Adrian and Brunnermeier (2011) extend the traditional VaR through the CoVaR, the prefix Co meaning conditional, contagion, or comovement. The CoVaR captures the loss of the whole financial system conditional on the distress of a financial institution. To obtain the ΔCoVaR, which represents the contribution of an institution to the system-wide risk, the authors compute the difference between the CoVaR obtained during a situation of distress for the institution and the CoVaR obtained during the median situation for the institution. Acharya et al. (2010) define the Marginal Expected Shortfall (MES) as well as the Systemic Expected Shortfall (SES). The marginal contribution of a financial institution captured by the MES is equal to the historical average of its daily equity returns when daily market returns are at their 5% or 1% lowest quantile.[5] The SES of an institution corresponds to its amount of equity which drops below its target level, in case of a systemic crisis. In other words, SES is the propensity of a financial institution to be undercapitalized when the system as a whole is undercapitalized. Brownlees and Engle (2012), Acharya, Engle and Richardson (2012) as well as Engle, Jondeau and Rockinger (2014) combine the MES with the market capitalization and the total amount of liabilities in order to build the SRISK. SRISK takes leverage and size into account and corresponds to the expected capital shortfall of a given financial institution, conditional on a substantial market decline.[6] The authors interpret the SRISK as a capital shortfall making a clear relationship with the regulatory purpose to increase financial stability through higher capital requirement. Still, using asset returns, Billio et al. (2012) focus on time series and propose a Granger-causality measure of interconnectedness (interpreted as a spillover effect) to assess systemic risk. In the same vein, Diebold and Yilmaz (2014) present several connectedness measures obtained using variance decomposition based on stock returns volatility data. The two previous studies identify the network topology. Corradin, Manganelli and Schwaab (2011) introduce a framework of multivariate regression quantiles to assess the contribution of a given financial institution. Straetmans and Chaudhry (2012) apply a statistical multivariate extreme value analysis to realize a cross Atlantic comparison of the financial system-wide risk. As explained by Markose et al. (2010), CDS had a pernicious role in the financial crisis and systemic risk measurement based on CDS data have been proposed, such as their Systemic Risk Ratio. Otherwise, Huang, Zhou and Zhu (2009) provide an estimated risk-neutral probability of default with the Distress Insurance Premium (DIP) index, whereas Giglio (2012) compute the joint default risk of financial institutions. Beyond this large but non-exhaustive collection of market-based systemic risk measures, another way to gauge the systemic contribution of a given financial institution exists.

The second subset of measures focuses on balance-sheet and regulatory data. Greenwood, Landier and Thesmar (2012), on the basis of data published by the EBA on the banks' exposures to the European sovereign debt, distinguish between the contribution of a given bank to financial sector fragility and its own vulnerability to systemic risk. Brunnermeier, Gorton and Krishnamurthy (2014) focus on liquidity to understand the crisis and argue that their Liquidity Mismatch Index (LMI) at the institutional level can provide valuable information to assess the systemic importance of a financial institution. As highlighted by Caballero (2010), systemic risk is intrinsically related to the degree of interconnectedness between financial institutions. Many studies follow this idea and

[5] Brownlees and Engle (2012) extend this measure to a time horizon of six months through the LRMES thanks to a conversion formula or multiple simulations.

[6] Engle and Siriwardane (2014) extend the SRISK by incorporating the structural GARCH model which proposes a new model of volatility where financial leverage amplifies equity volatility.

model the financial system as a network to quantify the contagion generated by linkages between financial institutions. Cont, Moussa and Santos (2012) present the Contagion Index, a metric for the systemic importance of financial institutions defined as the expected loss to the network triggered by the default of an institution in stress scenario. In their work, the systemic importance is based on counterparty exposures. Gouriéroux, Héam and Monfort (2012) also use a unique dataset of interbank bilateral exposures. Their methodology can separate the direct effects of a shock (such as a common asset shock or a specific shock to one bank) from the effects of contagion within the banking system. Identifying the most sensitive links is also the goal of Demange (2011), that is why he uses the Threat Index which reflects an externality imposed by a defaulting bank on the debt repayments of all other banks. This indicator is an alternative measure to the contagion risk of a bank, most of the time defined as the expected number of subsequent failures following its initial bankruptcy (see Upper 2011 for a survey). This identification methodology underlines that the contagion risk is not a one-dimensional issue. The network topography also matters, as emphasized by Acemoglu, Ozdaglar and Tahbaz-Salehi (2014) who shed light on the “robust yet fragile” (Haldane, 2009) nature of financial networks, meaning that a type of network can be very resilient to one type of shock but fragile under another.

This dissertation relies on a small subset of these individual systemic risk measures. The chosen sample is composed of the following measures: MES, SES, SRISK and ΔCoVaR. This choice has been guided by their nice economic interpretations, the public availability of data, and the real-time investigation allowed by these market-based systemic risk measures. My purpose is then to contribute to the literature which attempts to verify whether or not these new individual systemic risk measures are well-designed to gauge the contribution of a given financial institution to the system-wide risk. Brunnermeier and Oehmke (2012) have also addressed this issue and they propose a definition of what a relevant systemic risk measure should be and argue that the allocation principle is primordial. In order to give a potential answer to this question, Brunnermeier and Cheridito (2013) suggest the SystRisk measure. An alternative approach is to develop an axiomatic framework for the measurement and management of systemic risk (Chen, Iyengar and Moallemi, 2013), as Artzner et al. (1999) have done for the individual risk measures. The approach presented in my dissertation is complementary to the two illustrated above since the abilities of these measures to identify SIFIs and to resume all characteristics of systemic risk in a single measure are compared.

Measuring systemic risk and identifying SIFIs requires an in-depth analysis of financial institutions. A significant part of the systemic risk can only be identified through a detailed analysis of common activities and strategies among financial institutions.

Commonality among Banks

Financial institutions contributing the most to systemic risk are subject to a tighter supervision. This means that market activities such as trading positions with their associated liquidity need and ongoing exposures are under scrutiny. Sound risk management is not a new pillar in the current regulation because internal models are already validated by regulators through the microprudential approach. However, supervisors are now aware of macroprudential issues, including the potential for systemic risk to arise from concentration risk and common exposures, even when institutions seem safe when considered individually (FSB, 2011a).

Correlated risk across banks is not rare and has several sources. First, banks have incentives to over-invest in specific asset classes and this result may be exacerbated by the current regulation. For instance, policy makers have asked that Credit Defaults Swaps (CDS) be now clear through central counterparties (CCPs), that could dramatically increase the system-wide collateral demand leading to potential destabilizing effects since only few types of assets are eligible as collateral within CCP frameworks, such as sovereign debt (Duffie, Scheicher and Vuillemey, 2014). Second, Hirshleifer, Subrahmanyam and Titman (1994) show that the sequential nature of information arrival has a significant impact on trading decisions. Investors who receive common and private information before others do, become short-term “profit-takers” and have a tendency to trade the same group of stocks. Third, Acharya and Yorulmazer (2007, 2008) argue that banks have a strong incentive to herd, especially small banks, in order to maximize their probability of bailout. This type of behavior from banks increases the likelihood of a systemic risk crisis and poses for regulators a too-many-to-fail problem.[7] Farhi and Tirole (2012) argue that private leverage choices depend on the anticipated policy reaction to the overall maturity mismatch. Thus, banks as a whole are doing too much maturity mismatch (too much short-term debt) leading to higher correlated risk.

To sum up, financial institutions have incentives to correlate their positions on the overvalued assets. However, these positions are not publicly disclose and only regulators are able to monitor the degree of commonality among banks from these common exposures.

Obviously, correlated risks are particularly problematic during financial crises. Indeed, as market volatility spikes, regulatory capital and collateral requirements tend to mechanically increase for financial institutions. In response, many banks are forced to liquidate their positions. Adrian and Shin (2014) empirically illustrate this aspect, showing that to maintain a constant probability of default, financial institutions adjust their

[7] Brown and Dinç (2009) provide an empirical analysis of the too-many-to-fail effect thanks to a study of bank failures in twenty-one emerging market countries in the 1990s. They show that this impact is robust to several factors, such as the too-big-to-fail effect.

risk exposures very sharply when the economic environment becomes more risky. Brunnermeier and Pedersen (2009) propose a model to explain the fact that market liquidity has commonality across assets, which further amplifies market volatility. Morris and Shin (1999) explain that correlated risk exposures (interdependence) across banks leads to higher volatility since financial institutions tend to sell the same assets at the same time. This blind spot leads to adverse feedback effects which may have dramatic consequences in a crisis period (Persaud, 2000). Herding behavior is hard to prove given the lack of reliable data. Allen, Babus and Carletti (2012) develop a theoretical model to analyze the interaction between asset commonality and funding maturity in generating systemic risk. Cai, Saunders and Steffen (2014) measure the similarity between the syndicated loan portfolios of two banks and they find positive correlation between this measure of banks' interconnectedness and various market-based systemic risk measures including SRISK and CoVaR.

Commonality across financial institutions matters, but there are no accurate tools to identify risk exposures at their firm-wide level, across business lines and to other financial institutions. This challenge remains without standard measures while the need for such a measure is fundamental. Indeed, financial instability could be reduced by imposing exposures limits to financial institutions on certain asset classes. In this dissertation, I an innovative tool measure of risk exposures is proposed. This implied measure of changes in risk exposures is obtained for a broad spectrum of risks and established at a bank level. This new methodology could be an accurate way to track commonality in risk exposures across banks and then prevent a potential build-up of systemic risk.

Assessing the systemic risk is still at its beginnings and the main goal of this dissertation is to contribute to this abundant and stimulating literature by proposing three essays on systemic risk.

Contributions

The first chapter fills in the gap existing in the identification of Domestic Systemic Important Banks (D-SIBs). This empirical chapter 1 offers an original adjustment of three systemic risk measures designed in a global framework to evaluate their abilities to identify D-SIBs as well as G-SIBs. Following the spirit of the Basel III agreement, this chapter also highlights the shortage of capital that a given bank may have when this financial institution is jointly identified as G- and D-SIB.

The second chapter provides a theoretical and empirical analysis of the major systemic risk measures (MES, CoVaR and SRISK) based on market data (daily returns). To do this, chapter 2 introduces a common framework and derive a number of theoretical properties on these measures. In particular, conditions under which the different measures lead to similar rankings of SIFIs. This theoretical analysis is complemented by an empirical analysis on a sample of ninety-four American banks.

The third chapter proposes an implied measure of banks' risk exposures to several risk factors. This new approach, described in chapter 3, extracts private information about the changes in banks' risk exposures at an aggregate level from public risk disclosures, i.e. VaR disaggregated by major risk factors. Using this measure, commonality among ten international banks is investigated.

Chapter 1: Where is the System?

Chapter 1, entitled "Where is the System?", provides a methodology to identify both D-SIBs and G-SIBs.[8] According to the fact that the usual market-based systemic risk measures, such as SRISK and ΔCoVaR, are well designed to identify G-SIBs, this chapter offers a simple adjustment of these measures to investigate the systemic risk contribution of a given bank at the domestic level and extract specific additional policy for D-SIBs as required by the Basel Committee on Banking Supervision (BCBS, 2012).

In this context, even when the system of reference changes, these measures cannot be used to distinguish between D-SIB and/or G-SIB. This result shows on the one hand that SRISK is mainly sensitive to the total amount of liabilities of the bank, which does not depend on the size of the system. On the other hand, ΔCoVaR is highly sensitive to the choice of the system which leads to a clear distinction between the domestic and the global level-playing field.

This issue is illustrated within the eurozone where the identification of D-SIBs is very important. In order to do so, this chapter shows that the difference between two SRISKs computed at the national and at the European level is a promising tool to identify D-SIBs and evaluate the potential shortage of capital that a bank may have when this bank is simultaneously considered as D-SIB and G-SIB.

Chapter 2: A Theoretical and Empirical Comparison of Systemic Risk Measures

Chapter 2, entitled "A Theoretical and Empirical Comparison of Systemic Risk Measures", provides a comprehensive comparison of the major market-based systemic risk measures (MES, SES, SRISK and ΔCoVaR) that are currently used by central banks and banking regulatory agencies due to their nice economic interpretations. Although the Financial Stability Board (FSB) states that the score, measuring the contribution of a financial institution to the system-wide risk have to reflect size, leverage, liquidity, interconnectedness, complexity, and substitutability. The findings of this chapter indicate that these measures fall short in capturing the multifaceted nature of systemic risk. So far, the research in this chapter constitutes the first attempt at comparing, both theoretically and empirically, these major systemic risk measures. The result obtained is that

[8]This article is published in *International Economics*.

most of the variability of these systemic measures can be captured by one market risk measure or a firm characteristic.

In a common framework, the analytical expressions of these measures allow to uncover the theoretical link between systemic risk and standard financial risks (systematic risk, tail risk, correlation and beta), as well as firm characteristics such as leverage and market capitalization. More precisely, it is shown that MES is highly related to the beta of a firm, ΔCoVaR is highly related to the Value-at-Risk (firm tail risk) whereas SRISK is related to the beta and the leverage. Conditions under which the different measures lead to similar rankings of SIFIs are also derived.

The theoretical analysis is completed by an empirical application focusing on a sample of ninety-four American banks over the period 2000-2010. Estimation methods from seminal papers are applied. It is shown that different systemic risk measures lead to identify different SIFIs. Moreover, the linear regression analysis shows that a one-factor model explains between 83% and 100% of the variability of the systemic risk estimates. In cross-section, MES and SRISK are explained by the traditional beta of a firm and its total amount of liabilities, respectively. In time series, ΔCoVaR is mainly explained by the VaR.

Chapter 3: Implied Risk Exposures

Chapter 3, entitled "Implied Risk Exposures", introduces an innovative answer to the data gap facing regulators and researchers.[9] Indeed, to better assess the evolution of the financial system, more data have to be disclosed by financial institutions (Cerutti, Claessens and McGuire, 2014). Even if the stress tests leading by the European Banking Authority (EBA) is a substantial opportunity to observe actual positions or risk exposures of banks, those tests are not done every year. To overcome this issue, this chapter develops the Factor Implied Risk Exposures (FIRE) methodology to infer banks' risk exposures from current public risk disclosures.

The originality of this technique is to show how to reverse-engineer traditional banks' risk disclosures, such as the Value-at-Risk (VaR), to obtain an implied measure of their exposures to equity, interest rate, foreign exchange, and commodity risks. As this chapter considers a broader spectrum of risks, it extends recent literature which focuses only on banks' exposures to interest rate risk, as investigated by Begenau, Piazzesi and Schneider (2013) as well as Landier, Sraer and Thesmar (2013). It is also shown that the factor structure for the volatility of equity, documented by Herskovic et al. (2014), is persistent across the four asset classes, which highlight a certain degree of commonality in volatility across the assets within a given asset class. The performance of the method used in this chapter is assessed by systematically comparing the implied risk exposures given by the FIRE methodology, with statements made by a large financial institution about its

[9]This article is forthcoming in the *Review of Finance*.

actual risk exposures in public filings. The biases on the implied exposures that could be induced by model risk and estimation risk are also studied by simulation.

The empirical application on ten large US and international banks shows that changes in risk exposures are negatively correlated with market volatility and changes in risk exposures are positively correlated across banks, which is consistent with banks exhibiting commonality in trading. The first finding suggests that banks actively manage their risk exposures according to market conditions, and this can be seen as an attempt to damper the procyclicality of their regulatory capital. The second finding indicates that banks rebalance their trading portfolios in a correlated way. However, a pool of large banks which have a growing common exposure to an asset class is a source of interconnectedness between financial institutions that increase the systemic risk, and this concern is particularly relevant for banking regulators.

Chapter 1

Where is the System?[10]

The aim of this paper is to determine the optimal size of the system (global, supranational or national) when measuring the systemic importance of a bank. Since 2011, the Basel Committee on Banking Supervision (BCBS) has tagged global systemically important banks (G-SIBs) and has imposed a higher regulatory capital of loss absorbency (HLA) requirement. However, the identification of G-SIBs may overlook banks with major domestic systemic importance, i.e. the domestic systemically important banks (D-SIBs). This paper describes how to adjust market-based systemic risk measures to identify D-SIBs. In an empirical analysis within the eurozone, we show that (*i*) the SRISK methodology produces similar rankings whatever the system used. However, (*ii*) the SRISK values greatly vary across systems, which calls for imposing the higher of either D-SIB or G-SIB HLA requirements. Finally, (*iii*) the ΔCoVaR methodology is extremely sensitive to the choice of the system.

1.1 Introduction

Since September 15, 2008 and the collapse of Lehman Brothers, extensive research has been done on systemic risk, considering its definition, measurement, or regulation. While there is no unanimous definition for systemic risk yet, most definitions agree on three points that are summarized in the 2001 G-10's definition:

> "Systemic financial risk is the risk that an event will trigger a loss of economic value or confidence in [sic] a substantial portion of the financial system that [sic] have significant adverse effects on the real economy."

Thus, a systemic event corresponds to a *trigger point* which causes *significant disruption in the financial system* and finally *spreads out to the real economy*. For instance, the initial shock can be the bankruptcy of a financial institution, which sets off wide turmoils propagating through the financial system and finally jeopardizing the local and/or global economy. The key element that concerns systemic risk is the identification of Systemically

[10]This chapter is based on Benoit (2014), published in *International Economics*.

Important Financial Institutions (SIFIs), which correspond to firms that threaten the system. The nature of the system is well addressed in the context of the United States because of its particularity as a federal state. However, in Europe, where we are faced with a sum of countries, the issue is much less obvious. Hence, considering global or domestic systemically important banks (G- or D-SIBs) does not lead to the same conclusions and raises numerous questions. Should we evaluate the contribution of a given financial institution to the risk of the system at a domestic, supranational, or global level? Is the list of SIBs identical if we change the system used in the analysis? Most importantly, which definition of the system should be used in the identification process of SIBs?

The objective of this paper is to determine the optimal size of the system when measuring the systemic importance of a bank. To answer the above questions which are crucial for banking regulators, we adjust market-based systemic risk measures, usually used to identify G-SIBs, to identify D-SIBs. This approach is closely tied to the current regulatory debate on systemic risk. Indeed, following a request made by the G20, the Financial Stability Board required an extension of the G-SIBs to include D-SIBs in October 2012. The Basel Committee on Banking Supervision (BCBS) published a framework for dealing with D-SIBs (BCBS, 2012) in line with its former methodology for assessing G-SIBs (BCBS, 2011-2013b). This country-by-country approach requires regulators to take into account a set of new bank-specific factors such as size, interconnectedness, financial institution infrastructure and complexity of a particular bank within its own financial system. BCBS emphasizes that national regulators should establish their own list of D-SIBs. By analogy, identifying the supranational-SIBs should be done by a supranational regulator while identifying the G-SIBs should be done by a global regulator which assesses the system in the global context like the BCBS currently does.

This top-down approach implies that additional capital and tighter monitoring of G-SIBs are of the utmost importance if we want to avoid a wave of major bankruptcies that would affect the entire global system. A G-SIB is usually so large, interconnected and non-substitutable that we cannot miss it in the identification process. However, the fact that a particular bank cannot be seen at the global level does not imply that its contribution to systemic risk is null. Thus a bank could be a D-SIB without being identified as a G-SIB and its impact on other domestic banks could be significant and eventually destabilize the local economy. This is why, a bottom-up approach should be adopted. Taking D-SIBs into account in elaborating the regulation is even more important if we think that, for a given bank, its systemic contribution is probably larger in its country than abroad. For this reason, BCBS requires national authorities to calibrate the level of Higher Loss Absorbency (HLA) needed for D-SIBs. Consequently, the identification of SIBs changes depending on the system we focus on.

To deal with domestic systemic risk, two fundamental questions have to be addressed. First, what is the nature and the magnitude of the initial shock to identify D-SIBs? Should we consider a global systemic event or a domestic shock? Second, what should be the *system*? What should be the optimal perimeter of the system as well as its specific risk factors and the number of banks to be taken into account? Should we investigate the same banks at the global and domestic levels? Should we use a multi-industry system or only the banking system? This paper aims to answer these questions. Another important aspect of the systemic risk debate concerns the optimal taxation of SIBs. Indeed, as in the polluter pays principle, negative externalities created by SIBs have to be internalized by themselves and not by the taxpayer. In maximizing their private benefits, individual banks may rationally choose outcomes that are suboptimal on the system-wide level because they do not take into account these externalities (BCBS, 2013b). Thus, two aspects are studied by the BCBC to reduce these externalities, on the one hand reducing the probability of failure of a SIB with the HLA requirement and on the other hand reducing the impact of the failure of a SIB by improving resolution plans (FSB, 2011a).

This paper contributes to the literature on the identification of D-SIBs in Europe. Despite the fact that the BCBS would like D-SIBs to be identified, only a few papers tackle this issue. Elsinger, Lehar and Summer (2006) use a few individual bank characteristics which are easily observable to measure risk at the level of the banking system. Acharya and Steffen (2012) rank European banks using the Systemic Expected Shortfall (SES) measure based on the Marginal Expected Shortfall (MES), leverage, and total assets. Engle, Jondeau and Rockinger (2014) propose an adjustment of the Systemic Risk Measure (SRISK) to identify the D-SIBs but their main focus is still on G-SIB identification. This paper uses public data and not private information as the BCBS does. The goal of this paper is to close the gap between the market-based systemic risk measure applied to identify the G-SIBs and the D-SIB identification.

The present paper puts forward a User-Guide to adjust the two major market-based systemic risk measures (SRMs) to the choice of the system, and highlight the consequences the choice of a system can have. This analysis relies on publicly available real-time data, using the Systemic Risk Measure (SRISK) of Brownlees and Engle (2012), Acharya, Engle and Richardson (2012) and Engle, Jondeau and Rockinger (2014), and the Delta Conditional Value-at-Risk (ΔCoVaR) of Adrian and Brunnermeier (2011). Indeed, these popular measures of systemic risk contribution are easily adjustable to different systems, and the values in the former measure are expressed as an amount of money, allowing users to quantify the amount of the higher loss absorbency required for a given SIB. To avoid time lag and obtain results in the same currency, this paper considers the eurozone countries over the last decade, and this constitutes the global level. The domestic level corresponds to each of the 10 member countries of this economic and monetary union.[11] The main findings of this paper are the following. First, it shows that (*i*) the SRISK measure produces similar rankings regardless of the system used. Second, (*ii*) the SRISK values vary significantly across system definitions, which underlines the importance of imposing the higher of either D-SIB or G-SIB HLA requirements. Third, (*iii*) the ΔCoVaR which mainly captures the degree of interconnectedness between a particular system and a bank that belongs to this system, is highly sensitive to the choice of the system.

The rest of the paper is organized as follows. Section 1.2 provides a brief literature review of systemic risk and introduces the general framework to identify G-SIBs and D-SIBs with their specific factors. Section 1.3 describes the SRISK and the ΔCoVaR methodologies. Section 1.4 presents the data and the main empirical findings. Section 1.5 offers a summary and a conclusion.

1.2 Principles for SIBs

This section sums up the two main approaches used to identify SIBs and shows that both are useful. Then its describes the assessment methodologies made by the BCBS to look for G- and D-SIBs.

1.2.1 Literature Review

In this paper, we do not want to oppose the two traditional approaches tackling systemic risk. In other words, we do not plan to dwell on the question of whether or not an approach may be more efficient. The first approach is only based on balance sheet and stock returns data (Acharya et al., 2010; Billio et al., 2011; Adrian and Brunnermeier, 2011; Acharya, Engle and Richardson, 2012; Brownlees and Engle, 2012), whereas the second approach requires balance sheet information disaggregated by class of assets and counterparties (Gouriéroux, Héam and Monfort, 2012, 2013; Greenwood, Landier and Thesmar, 2012). Furthermore, the Shapley Value can be applied to the two former approaches (Borio, Tarashev and Tsatsaronis, 2010; Drehmann and Tarashev, 2011a; Garratt, Webber and Willison, 2012; Gauthier, Lehar and Souissi, 2012; Cao, 2010). However, as this paper shows, there is an additional issue. Danielsson et al. (2011) argue that these systemic risk measures contain a high degree of model risk due to their dependence to the VaR (or ES) which is a noisy riskometer. Our extra model risk is linked to the mathematical definition of the market index because this latter could be capitalization-weighted or equally weighted for example. We are going beyond this simple index construction issue because we use this matter to focus on the optimal size of the system and so transform it as a force of these market-based SRMs to enhance their ability to identify D-SIBs.

[11] Established in January 1, 1999, the eurozone is an economic and monetary union of 17 European Union member states (in November 2012) which have shared a single currency, the euro, since January 1, 2002.

The common feature of these different methods is that they are already included within a particular system which is interesting since the size of the network is particularly important to capture the degree of interconnectedness of a given financial institution with its neighbor. For example, Lopez-Espinosa et al. (2012a) derive the CoVaR at a global level whereas Cerutti, Claessens and McGuire (2014) emphasize the need for additional data to capture international dimensions of systemic risk. In contrast, Elsinger, Lehar and Summer (2006) and Acharya and Steffen (2012) apply Marginal Expected Shortfall, Conditional Expected Shortfall and Systemic Expected Shortfall at the European level. The only paper that focuses on domestic level, from Brämer and Gischer (2011), adjusts the indicator-based approach proposed by the BCBS and identifies D-SIBs in the context of the Australian banking system. Engle, Jondeau and Rockinger (2014) design a specific econometric multi-factor model to address asynchronous markets. To identify G-SIBs and D-SIBs among European financial banks with this new model, they explain the bank's return by three drivers, a country-wide index, an European index and a world index. One of the contributions of this paper is to show that this multivariate model does not outperform the traditional bivariate model when the identification of D-SIBs is the purpose.

1.2.2 G-SIBs Assessment

To assess the global systemic risk based on data related to the consolidated group, BCBS has developed a framework (Financial Stability Board - International Monetary Fund - Bank for International Settlements, 2009; BCBS, 2013a; FSB, 2011b; Financial Stability Oversight Council, 2012a) which incorporates a score based on systemic risk factors such as cross-jurisdictional activity, size, interconnectedness, substitutability/financial institution infrastructure and complexity (for a complete description, see BCBS, 2011a, 2013b). BCBS's view is that global systemic importance should be captured as a Loss-Given-Default (LGD) concept, which measures the systemic impact that a bank's failure may have on the global financial system and the wider economy, rather than the probability of such a bank's failure, which refers to the Probability of Default (PD) concept. Then, following an indicator-based measurement approach, banks get a score. This number defines the bucket in which they are thrown depending on their position regarding the cutoff points which delimitate the bucket size. Given the bucket, a specific amount of HLA is required. This G-SIB's HLA requirement, which is a minimum amount, will be added to the Common Equity Tier One of the G-SIB and correspond to a percentage of its Risk-Weighted Asset.

In addition to this bucketing approach based on the clustering of scores produced by the methodology, an approach leading to a capital surcharge, addressing systemic risk also implies being careful with the behavior of those banks. With this risk, the global financial system faces moral hazard, and being a G-SIB can be viewed as a good opportunity because banks are sure to be well capitalized and more intensively monitored. However, this surcharge can be viewed either as a blessing or a punishment because financial institutions are explicitly too big and/or too interconnected to be saved (Markose et al., 2010), and have to quickly raise new capital, which can be very expensive. Even if banks wanted to reduce their contribution, they would have no strong incentive to do so. Indeed, their funding cost would increase and the reduction of their risk means a loss in the return of their market share, then these global actors become less competitive and could face opposition from shareholders against this strategy. With this public list of G-SIBs, banks have an explicit guarantee from a government support which may amplify risk-taking, reduce market discipline, create competitive distortions and so increase the probability of distress of those banks. For these reasons, a tightly additional supervision has been requested. Ancillary quantitative indicators relating to specific aspects and a supervisory judgement based on qualitative information are also used to gauge the potential effect of a G-SIB (BCBS, 2013b). For example, in 2011, 27 banks were identified by the score indicator and 2 have been added based on home supervisory judgement (BCBS, 2011a, 2013b).

Based on this regulatory framework, Table 1.1 reports the worldwide list of G-SIBs published by the Financial Stability Board in 2011 using data as of end-2009.[12] When the SRISK is presented by its authors at a conference, they argue that this measure is close to this list of G-SIBs and show that the ranking which is obtained with the SRISK is not linked to the leverage, the MES (measure of interconnection) and the size (captured by the market capitalization). Unsurprisingly, SRISK allows to identify 23 out of 29 of these G-SIBs. Moreover, using this measure it is possible to pinpoint which banks are the riskiest. However we show that, at this date, the ranking based on the quarterly book value of liabilities reports 26 out of 29 of these G-SIBs, whereas 25 banks can be found both in the SRISK and the quarterly book value of debt lists.[13] In presenting this table, our point is not to argue about the identification of G-SIBs, which is carefully done by the regulator using a thorough methodology to assess systemic risk. Instead, we just want to point out that a market model-based approach to estimate the contribution of individual bank to systemic risk (such as the SRISK) is not far from the BCBS output and could be an useful measure to proxy the systemic contribution of a given firm while this quantity is close to the total amount of liabilities. The SRISK is a daily measure designed to gauge the expected capital shortfall that a given bank may have during a *global financial crisis*. This quantity can be adjusted to deal with a *domestic financial crisis* and thus to potentially identify D-SIB. However, the SRISK as well as the MES and the ΔCoVaR

[12] An updated list of G-SIBs published in 2012 (Financial Stability Board, 2012), where two banks have been added to the list (BBVA and Standard Chartered) and three removed (Commerzbank, Dexia and Lloyds, is available).

[13] According to the updated list of G-SIBs published in 2012 based on end of 2011 data, the SRISK and the quarterly book value of liabilities identify 21 out of 28 G-SIBs tagged by the BCBS whereas the SRISK and the quarterly book value of liabilities rankings have 25 institutions in common among the first 28 G-SIBs.

remain concerned by the robustness of its results. Danielsson et al. (2012) point out that the signal provided by the MES and the ΔCoVaR is highly unreliable and conclude that

Table 1.1 Systemic Risk Rankings: G-SIBs

December 31, 2009		
	G-SIBs	
FSB	SRISK	Liability
Bank of America	Royal Bank of Scotland	BNP Paribas
Bank of China [2, 3]	BNP Paribas	Royal Bank of Scotland
Bank of New York Mellon [2, 3]	Deutsche Bank	Deutsche Bank
Banque Populaire CdE [2, 3]	Group Crédit Agricole	HSBC
Barclays	Barclays	Group Crédit Agricole
BNP Paribas	Mitsubishi UFJ FG	Mitsubishi UFJ FG
Citigroup	Mizuho FG	Barclays
Commerzbank	ING Bank	Bank of America
Credit Suisse	Lloyds Banking Group	JP Morgan Chase
Deutsche Bank	Commerzbank	Citigroup
Dexia	Citigroup	Mizuho FG
Goldman Sachs [2]	Société Générale	ING Bank
Group Crédit Agricole	UBS	Lloyds Banking Group
HSBC	Sumitomo Mitsui FG	Santander
ING Bank	HSBC	Société Générale
JP Morgan Chase	Unicredit Group	UBS
Lloyds Banking Group	Bank of America	Unicredit Group
Mitsubishi UFJ FG	Dexia	Commerzbank
Mizuho FG	Santander	Sumitomo Mitsui FG
Morgan Stanley	Credit Suisse	Wells Fargo [2]
Nordea	JP Morgan Chase	Credit Suisse
Royal Bank of Scotland	Natixis [1, 3]	Intesa Sanpaolo SpA [1]
Santander	Danske Bank A/S [1]	Dexia
Société Générale	Morgan Stanley	Goldman Sachs [2]
State Street [2, 3]	Intesa Sanpaolo SpA [1]	Banco Bilbao V. A. [1]
Sumitomo Mitsui FG	Nordea	Morgan Stanley
UBS	KBC Groep NV [1, 3]	Nordea
Unicredit Group	Banco Bilbao V. A. [1]	Danske Bank A/S [1]
Wells Fargo [2]	Resona Holdings [1, 3]	National Australia Bank [1, 2]

Sources: FSB and V-Lab website. *Notes:* In the first column, labeled FSB, we report the list in alphabetic order of the 29 G-SIBs identified according to the methodology set out in the BCBS document "Global systemically important banks: Assessment methodology and the additional loss absorbency requirement", using data as of end-2009. To be fair we report, in the second column labeled SRISK, the publicly available ranking (available on the VLab website) of the first 29 G-SIBs identified by the SRISK measure on December 31, 2009. In the third column, labeled Liability, we disclose the ranking based on the total amount of liabilities dated from December 31, 2009. The following [1] tags banks which are not identified by the FSB, [2] tags banks which are not identified by the SRISK and [3] tags banks which are not identified by the total amount of liabilities.

a leverage ratio may offer a more sensible approach to deal with systemic risk. Drehmann and Tarashev (2011b) argue that simple indicators are able to gauge some aspects of systemic risk and Benoit et al. (2013) show that the SRISK does not encompass the multiple facets of systemic risk. In this case, the identification of G-SIB is mainly driven by the total amount of liabilities because at this global level, principal actors are large banks which are well-known worldwide.

Dealing with systemic risk means taking the multifaceted threat into account, and one of the main issues is probably not the identification of G-SIBs since one could reproduce almost every single future list of G-SIBs using only a combination of simple indicators such as the amount of liabilities and the leverage. The principal identification issue arises at a domestic level, where the number of banks which are concerned is different. Indeed, at the worldwide level, the 75 largest global banks based on the financial year-end Basel III leverage ratio exposure measure exceeding the threshold of 200 billion euros (BCBS, 2013a), are taken into account, as well as banks that have been classified as a G-SIB the previous year are included in the sample (BCBS, 2013b). At the domestic level, this number is smaller and at least the size indicator of the bank has to be updated. Furthermore, the degree of interconnection is certainly thinner and therefore difficult to be easily captured. Thus, the BCBS methodology as well as market-based SRMs have to be modified according to the domestic level-playing field.

1.2.3 D-SIBs Assessment

A set of 12 principles composes the D-SIB framework (BCBS, 2012). The two key aspects that shape this methodology are:

1. the reference system for the assessment of systemic impact; and
2. the unit of analysis, i.e. the bank which is being concerned.

The Committee responds clearly to these questions, the appropriate reference system should be the domestic economy whereas the unit of analysis are banks from a (globally) consolidated perspective. In other words, the localization of the systemic risk event is the *domestic market* and its magnitude has to be calibrated to the country specifics. Banks' subsidiaries are studied at the consolidated state when its banking group is hosted by the domestic jurisdiction. Indeed, a banking group involved in cross-border activities potentially has significant spillovers to the domestic economy when its subsidiaries fail. In contrast with the host authorities which have to assess these foreign subsidiaries at a local level or sub-consolidated basis from their domestic economy. For example, Emporiki Bank was a Greek subsidiary of Crédit Agricole until 2012, from the French authority Crédit Agricole has to be studied at the consolidated perspective, i.e. taking into account Emporiki Bank's activities. But from the Greek authority point of view, Emporiki Bank is in its scope as well as all its foreign subsidiaries but Crédit Agricole is not.

The D-SIB methodology is designed as the G-SIB approach, 4 bank-specific factors are used instead of 5, size, interconnectedness, financial institution infrastructure and complexity. The size of the domestic economy is also required because countries with a larger banking sector relative to GDP are more likely to suffer from a D-SIB failure in its own jurisdiction. Banks can be classified as D-SIBs but not as G-SIBs when their domestic activities have no impact on the global economy but only on the domestic financial system. A bank identified as a G-SIB can also be classified as a D-SIB in any of the countries in which the bank has significant operations. However, banks with large global operations can be classified as a G-SIB but not as a D-SIB if those activities have no significant impact in any domestic economy (Deloitte, 2013). When the banking group has been identified as a G-SIB as well as a D-SIB in the home jurisdiction, the national authorities should impose the higher of either the D-SIB or G-SIB HLA requirements (BCBS, 2012). Indeed, the BCBC is setting minimum standards of capital, so an asymmetric treatment is set out for banks which are not G-SIBs but D-SIBs or both at the same time.

For a given bank, one could argue G-SIB HLA has to be higher than the D-SIB HLA because at the global level, the totality of its interconnections are known and not only its domestic linkages. Thus a global shock should lead to a bigger HLA requirement. However, the marginal effect of this global shock is less than the domestic shock, a global shock is more spread out than the domestic shock. As in an earthquake where the seismic magnitude and damages are greater the closer you are to the epicenter, the D-SIB HLA has to be higher than the G-SIB HLA when you face a domestic shock. Moreover, D-SIB can be viewed as the worst case because a bank is penalized although it is not a global actor. Banks identified as domestic actors probably want to grow until becoming principal actors but their growth is reduced due to the HLA requirement. However, given the repartition of systemic risk in five equal parts, 20% for each systemic risk factor in the G-SIB methodology, a bank could reduce one of those factors to increase its degree of interconnectedness and become a global actor without being further penalized. So far, no incentives have been considered to reduce the degree of interconnectedness or common exposure of a given financial system to an exogenous source of risk, which is the key element of systemic risk at a domestic level.

At the domestic level, Brämer and Gischer (2011) replace the cross-jurisdictional activity by the Domestic sentiment. Another attempt has been made by Engle, Jondeau and Rockinger (2014) to identify D-SIB with the SRISK measure. Even if they have worked at the consolidated perspective for each bank, they have used their classic SRISK divided by the GDP of the country to identify D-SIB and so compare and rank banks at the European level according to their adjusted SRISK. However, to accurately deal with D-SIB two modification have to be done. First a domestic shock, not a global one should be applied. Thus, their DRISK has to be preferred to their SRISK. Second, adjusting the SRISK figures according to the current GDP has no impact on the domestic ranking of banks because the denominator is the same for banks of a given country. They only highlight the size of the banking sector in the national economy although it would be promising to observe whether or not the national ranking of a given bank differ according to the localization and the magnitude of the shock (global or domestic).

In this paper, we compute market-based systemic risk measures using publicly available data. We assume market efficiency because system bank-specific factors need to be included into the market return, which is the only element to gauge the choice of the system. The eurozone is an ideal example to challenge all SRMs because it implies taking into account not only national specifics but also supranational authorities like the European Central Bank (ECB), which is in charge of the monetary policy. Furthermore, dealing with national specifics becomes more and more important during a financial crisis because each country wants to protect its own banking system to avoid bank runs (Diamond and Dybvig, 1983).

1.3 Systemic Risk Measures

In this section, we present the SRISK and the ΔCoVaR which capture the contribution of a given bank to the risk of the system, both at a European (supranational) and domestic (national) levels. These measures are derived from a unified framework described in Appendix 1.6.1 and we show how to adjust both measures to deal with the perimeter of the system as well as the localization and the magnitude of the shock to evaluate the systemic contribution of E- and D-SIBs.

1.3.1 SRISK

The SRISK measure proposed by Brownlees and Engle (2012) and by Acharya, Engle and Richardson (2012) and finally by Engle, Jondeau and Rockinger (2014) extends the Marginal Expected Shortfall (MES) measure taking into account both the liabilities and the size of the financial institution, i.e. its financial leverage. The SRISK corresponds to the expected capital shortfall of a given financial institution, conditional on a crisis affecting *a particular system*. In other words, the SRISK is the difference between the required capital and the available capital. In this perspective, banks with the largest capital shortfall are assumed to be the greatest contributors to the crisis. Hence, banks which are not well capitalized are considered the most systemically risky. The SRISK is defined as:

$$SRISK_{it} = k\ D_{it} - (1-k)\ (1 - LRMES_{it})\ W_{it}\ , \tag{1.1}$$

where k is the prudential capital ratio of equity to assets, D_{it} is the quarterly book value of total liabilities, and W_{it} is the daily market capitalization or market value of equity.[14] The prudential capital ratio k is usually set to 8% but may vary from bank to bank due to different accounting standards. A well-known example is the divergence observed between U.S. GAAP and international IFRS accounting systems which could lead to specific k component.[15] In this eurozone study, accounting standards are the same and prudential capital ratio is fixed at 8% as in Engle, Jondeau and Rockinger (2014). This systemic risk measure also considers the interconnection of a bank with the rest of a *particular system* through the long-run marginal expected shortfall (LRMES) which captures the sensitivity to bank's equity return to *particular market shocks*. The LRMES is based on MES and corresponds to the drop in the equity value the bank should face when the *particular market* falls by more than its Value-at-Risk (VaR). Acharya, Engle and Richardson (2012) propose to approximate the LRMES, without simulation, using the daily MES, described in Appendix 1.6.2, as $LRMES_{it} \simeq 1 - \exp(18 \times MES_{it})$. This approximation represents the bank expected loss per dollar at a time horizon of six months, conditional on this *particular market* falling by more than 40% in the next 6-months period (see Appendix 1.6.3). As a consequence, Eq. (1.1) is the subtraction of two terms, the first part being the non-MES component whereas the second part is the MES component varying according to the level-playing field.

The useful property of this SRM is that this measure is strongly linked to the choice of the system with the MES component. Thus, Eq. (1.1) can easily be adapted according to the level of the regulation that is dealt with. When we focus on G-SIBs identification as the BCBS does, we consider a *global system* which means *global market*. Thus, as argued by the BCBS when the system of reference changes, the *market return* used has to be modified. In this paper, *supranational level* represented by the *eurozone area* is studied and Eq. (1.1) becomes:

$$SRISK_{it}^{E} = k\ D_{it} - (1-k)\ (1 - LRMES_{it}^{E})\ W_{it}\ , \tag{1.2}$$

able to identify E-SIBs. Similarly when we focus on the D-SIBs as the national authorities in charge of the regulation do, we consider a *national system* which means *domestic market* and obtain the following expression:

$$SRISK_{it}^{D} = k\ D_{it} - (1-k)\ (1 - LRMES_{it}^{D})\ W_{it}\ . \tag{1.3}$$

The two quantities given by Eqs. (1.2) and (1.3) can be expressed in the same currency. This analysis is not exposed to a currency mismatch or time lag issue because it is an eurozone investigation. Indeed, the SRISK amount, to be comparable, has to be adjusted according to the exchange rate, when considering a global level where currencies are still

[14] As defined in Appendix 1.6.3, the true definition of the SRISK is given by Eq. (1.36) with the max operator, but we work with the difference of two SRISK in the empirical illustration. Thus, we do not impose this minimum threshold to obtain the magnitude in the change of the capital shortfall.

[15] The V-Lab website sets to 5.5% the prudential capital ratio for Europeans financial institutions instead of 8% for those from the rest of the world, http://vlab.stern.nyu.edu/analysis/RISK.WORLDFIN-MR.GMES.

linked to a sovereign monetary policy. Because both quantities are comparable for a given bank, the difference between the two can easily be computed:

$$SRISK_{it}^{D} - SRISK_{it}^{E} = (1-k)\ (LRMES_{it}^{D} - LRMES_{it}^{E})\ W_{it}\ . \tag{1.4}$$

Eq. (1.4) captures the shortage of HLA that a given bank may have when this financial institution is jointly identified as E- and D-SIB. Then, a *domestic effect* is observed when SRISK^D > SRISK^E whereas a *eurozone effect* arises whether SRISK^E > SRISK^D. While an anticipated SRISK^D greater than SRISK^E due to lower degree of connection of a bank with its supranational system is likely to happen, the reverse cannot be out of the scope. In other words, bank i should be more affected by the downturn in its *domestic market* than the drop in its *supranational market* except when the bank owns a lot of subsidiaries abroad (in this case especially in the supranational area) and when its degree of openness to foreign activities is large.

Engle, Jondeau and Rockinger (2014) argue that for a domestic crisis, a semiannual crash of 40% is much more severe in Switzerland than in Hungary due to wide discrepancies in the domestic market volatilities from one country to the other. Moreover, to identify E- and D-SIBs, the conditional crisis has to take place in the supranational and national market, respectively. To deal with these two points and according to Appendix 1.6.2 and 1.6.3, the LRMES is written as:

$$LRMES_{it}^{D/E} = 1 - \exp\left(18 \times MES_{it}(\alpha)^{D/E}\right)\ , \tag{1.5}$$

where $MES_{it}(\alpha)^{D/E}$ captures the specific market conditions.[16]

To estimate the systemic contribution given by the SRISK, we use a DCC-GARCH model as Brownlees and Engle (2012) did, and apply a nonparametric kernel estimation method (Scaillet, 2005) to estimate conditional expectations.[17]

1.3.2 ΔCoVaR

The ΔCoVaR measure proposed by Adrian and Brunnermeier (2011) extends the VaR methodology because it allows computing VaR depending on a specific event. The ΔCoVaR of bank i is defined as the difference between the VaR of a *particular system* conditional on the distress of bank i, and the VaR of this *particular system* conditional on bank i being in its median state. A financial institution is in distress when its loss is equal to its VaR at the α% level of risk, and in normal state if its loss is equal to its

[16] See Appendix 1.6.3 for a broader discussion about the SRISK measure.

[17] We model the conditional variances σ_{it}^2 and σ_{mt}^2 according to the asymmetric TGARCH specification (Rabemananjara and Zakoïan, 1993) and so deal with the heteroskedasticity, and use a DCC model (Engle, 2002) for the time-varying correlations ρ_{it}. The model is estimated in two steps using Quasi Maximum Likelihood. In the kernel estimation, we set the bandwidth at $T^{-1/5}$ and choose the standard normal probability distribution function as a kernel function, i.e. $k(u) = \phi(u)$.

median return. Thus, the ΔCoVaR is defined as:

$$\Delta CoVaR_{it} = CoVaR_{it}^{m|r_{it}=VaR_{it}(\alpha)} - CoVaR_{it}^{m|r_{it}=Median(r_{it})} \tag{1.6}$$
$$= \gamma_{it} \ [VaR_{it}(\alpha) - VaR_{it}(0.5)] \ , \tag{1.7}$$

where γ_{it} corresponds to the linear projection coefficient of *a particular market* return on the bank return. This proportionality coefficient is fundamentally linked to the correlation between bank and market returns and market volatility. Appendix 1.6.4 describes Eq. (1.7) in detail and gives the explicit expression for γ_{it}. Like the MES, the ΔCoVaR is a measure of interconnectedness, both quantities are mainly driven by the return correlation and this coefficient is different for a *particular system*. So once again, we can derive two ΔCoVaRs according to the level of the system. For the *global system*:

$$\Delta CoVaR_{it}^{E} = \gamma_{it}^{E} \ [VaR_{it}(\alpha) - VaR_{it}(0.5)] \ , \tag{1.8}$$

and for the *domestic system*:

$$\Delta CoVaR_{it}^{D} = \gamma_{it}^{D} \ [VaR_{it}(\alpha) - VaR_{it}(0.5)] \ . \tag{1.9}$$

With the ΔCoVaR, we can compare those quantities separately without being able to subtract them because they are computed for different system aggregate levels. On the one hand, Eq. (1.8) is a difference between two CoVaRs of the *global market* returns and on the other hand, Eq. (1.9) is a difference between two CoVaRs *domestic market* returns. As a consequence, we cannot subtract these two conditional quantiles. To estimate systemic contributions, ΔCoVaR^E and ΔCoVaR^D, we also use a DCC-GARCH model.[18]

1.3.3 Correlation

SRISK and ΔCoVaR capture the interconnectedness of a given bank i to a particular system through the correlation between banks and a *specific market* returns. This is the single element directly connected to the market. Thus, as soon as the level-playing field is changed, the correlation also changes and affects SRMs.

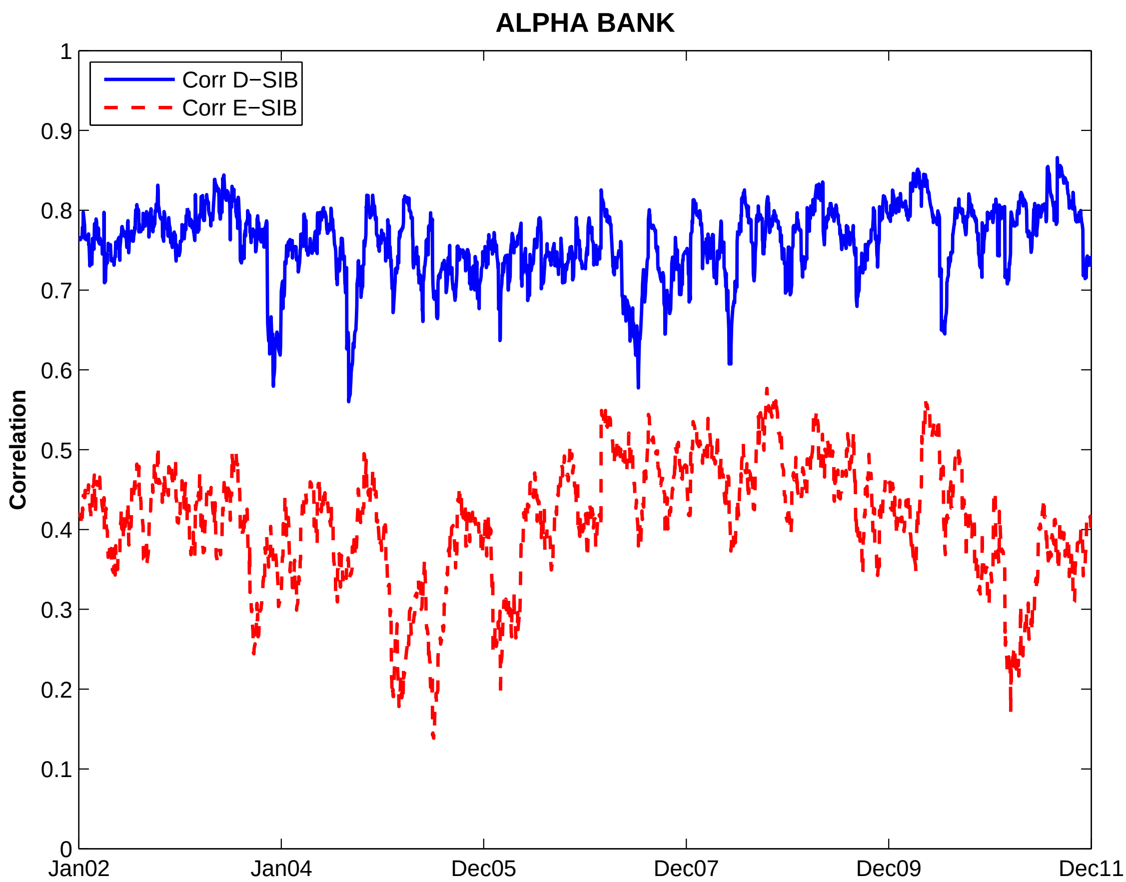
Figure 1.1 displays the time series evolution of the conditional correlation of Alpha Bank.[19] As expected, the return correlation of this bank with its domestic market is higher than its return correlation with the global index. We observe specific changes at some point, especially at the European level, because the bank is less connected with this index. Thus, is return correlation able to capture all aspects of systemic risk regardless

[18] We can also apply a quantile regression of the market return on the firm's return of a given bank as in Adrian and Brunnermeier (2011) and obtain a γ_i coefficient which is constant over time. In the rest of the paper, we report ΔCoVaR estimated with DCC-GARCH because results are robust to any the methodology applied. Results obtained with quantile regression without macro-variables are available upon request.

[19] Alpha Bank is the 3^{rd} bank in Greece and the 273^{th} largest bank worldwide according to the amount of assets at the end of 2011.

of the chosen level of the system? The purpose of the next section is to provide some answers at this question with an empirical illustration.

Figure 1.1 Conditional correlation of Alpha Bank return



Notes: This figure displays the conditional correlation of Alpha Bank return with its domestic index (blue solid line) and with its eurozone index (red dashed line). The estimation period is from 01/02/2002 to 12/30/2011.

1.4 Empirical Results

In this section, we implement and comment on an empirical study on the systemic risk for the eurozone area. A cross-sectional and time series analysis of the results follows a brief description of the dataset.

1.4.1 Dataset

A sample of 42 European banks belonging to 10 countries has been collected. The careful choice of these banks was conditioned by the fact that they are all included in the market indexes representing the entire economy (domestic and eurozone) and not only banking system, provided by Deutsche Börse on its website with the STOXX indexes. In this empirical investigation, 11 market indexes, one per country (domestic system) plus 1 for the eurozone market (global system) are required. The first step to collect this dataset is to access to the EURO STOXX Total Market Index (TMI) which is the eurozone index.[20] The second step is selecting the EURO STOXX TMI components and having the list of its composition. The final list of the banks is obtained after filtering, e.g. Banque Nationale de Belgique and Bank of Greece are excluded due to their national central bank status (see Appendix 1.6.5). This list, being composed of banks coming from 10 different countries, enables me to extract 10 domestic STOXX TMI of their respective countries.[21] This website allows the download of these market prices from January 1, 2002 to December 30, 2011 whereas stock prices, annual amount of liability in book value and daily market value of equity are extracted from Datastream Worldscope over the same period, which is the third step. Finally, we have computed the log-returns on these stock prices and market index prices. Unfortunately, no information about the weight of the components of these indexes is available and the sample of the 42 selected banks is not large enough to identify all D-SIBs for each Eurozone countries.[22]

The list of banks is constant for any chosen level of the system because we focus on the evolution of our SRMs according to the choice of the system. Banks' data are obtained at the banking group consolidated perspective and hosted by a single host country. None of these banks are a subsidiary. Of course, for a given country, the set of banks should increase at a domestic level because the number of potential D-SIBs grows when the size of the system is reduced, i.e. smaller bank should be included. To assess these changes we have performed a cross-sectional analysis to observe if the ranking is consistent across the system aggregate level. Using time series analysis we also look at the difference between domestic and global SRM.

1.4.2 Cross-section

This cross-sectional analysis mainly allows to compare rankings delivered by SRISK and ΔCoVaR when we adjust the level-playing field for their implementation.

Table 1.2 reports the amount (Value), the domestic ranking (Rank^D) and the eurozone ranking (Rank^E) of all banks based on the SRISK^D, SRISK^E on December 31, 2011. Domestic and eurozone rankings produced by the SRISK^D are identical to those produced by the SRISK^E. This result is the same as in Engle, Jondeau and Rockinger (2014), where they rank European financial institutions by SRISK in percentage of domestic nominal Gross Domestic Product (GDP). However, this output could be considered as lacking reliable since we have no additional information to be extracted from the domestic ranking. Indeed, even if the localization and the magnitude of the shock are adjusted do deal with specific factors, rankings remain unchanged which would not be the case with

[20]This link sends users to the STOXX website, and precisely on the EURO STOXX Total Market Index page, http://www.stoxx.com/indices/index_information.html?symbol=BKXE .

[21]This link sends users to the STOXX website, and precisely on the STOXX Austria Total Market page, http://www.stoxx.com/indices/index_information.html?symbol=TCATP .

[22]The dataset has been done in July 2012, the current bank's components of this EURO STOXX TMI index are different but the steps of the sample composition stay the same.

Table 1.2 SRISK Systemic Risk Rankings per country and over the eurozone

December 30, 2011						
Bank's Name	SRISK^D			SRISK^E		
	Value	Rank^D	Rank^E	Value	Rank^D	Rank^E
Austria						
ERSTE GROUP BANK	13,720	1	15	13,313	1	15
RAIFFEISEN BANK INTERNATIONAL	9,480	2	19	9,258	2	19
OBERBANK AG	192	3	42	192	3	42
Belgium						
DEXIA	32,819	1	10	32,840	1	10
KBC GRP	19,727	2	12	19,735	2	12
Germany						
DEUTSCHE BANK	157,482	1	1	157,718	1	1
COMMERZBANK	47,953	2	7	48,106	2	7
DEUTSCHE POSTBANK	10,764	3	17	10,851	3	17
Spain						
BCO SANTANDER	66,958	1	5	65,993	1	5
BCO BILBAO VIZCAYA ARGENTARIA	29,003	2	11	28,203	2	11
BANKIA	18,161	3	13	18,051	3	13
CAIXABANK	11,079	4	16	11,002	4	16
BCO POPULAR ESPANOL	7,201	5	23	7,088	5	23
BCO SABADELL	4,884	6	27	4,742	6	27
BANCA CIVICA	4,442	7	28	4,474	7	28
BANKINTER	3,230	8	33	3,202	8	33
Finland						
POHJOLA BANK	2,269	1	35	2,263	1	35
France						
BNP PARIBAS	138,102	1	2	138,076	1	2
CREDIT AGRICOLE	130,007	2	3	129,985	2	3
GRP SOCIETE GENERALE	85,976	3	4	85,927	3	4
NATIXIS	37,049	4	9	37,027	4	9
Greece						
NATIONAL BANK OF GREECE	8,054	2	22	7,799	2	22
EFG EUROBANK ERGASIAS	5,949	3	25	5,912	3	25
ALPHA BANK	4,437	4	29	4,396	4	29
PIRAEUS BANK	3,920	5	30	3,913	5	30
BANK OF ATTICA	290	6	40	279	6	40
Ireland						
BANK OF IRELAND	10,639	1	18	10,500	1	18
Italy						
UNICREDIT	65,162	1	6	64,455	1	6
INTESA SANPAOLO	40,134	2	8	39,228	2	8
BCA MONTE DEI PASCHI DI SIENA	17,022	3	14	16,915	3	14
BCO POPOLARE	9,096	4	20	8,999	4	20
UBI BCA	8,520	5	21	8,464	5	21
BCA POPOLARE EMILIA ROMAGNA	3,709	6	31	3,667	6	31
BCA POPOLARE DI MILANO	3,379	7	32	3,367	7	32
BCA CARIGE	2,026	8	36	1,941	8	36
CREDITO EMILIANO	1,880	9	37	1,842	9	37
CREDITO VALTELLINESE	1,776	10	38	1,763	10	38
BCA POPOLARE DI SONDRIO	921	11	39	883	11	39
CREDITO BERGAMASCO	224	12	41	228	12	41
Portugal						
BCO COMERCIAL PORTUGUES	6,606	1	24	6,510	1	24
BCO ESPIRITO SANTO	5,251	2	26	5,042	2	26
BCO BPI	3,096	3	34	3,070	3	34

Notes: This table displays the bank's name in the first column, the second and third column are divided in three small columns with results based on SRISK^D and SRISK^E values, respectively. The small column on the left reports SRISK figures in million euros, the middle one discloses the rank of the bank in its country whereas the right column flags the eurozone rank of the bank (number 1 corresponds to the riskiest bank). Rankings are dated from December 30, 2011.

rankings extracted when a stronger eurozone shock is applied. When we follow Engle, Jondeau and Rockinger (2014), we obtain a different eurozone ranking (Rank^E) due to their SRISK adjustment by the domestic GDP that we do not make, but we would argue that the identification of potential D-SIBs would be more thoroughly accomplished if the domestic rankings (Rank^D) that are used were different when the shock takes place in the national system, instead of using identical domestic rankings with and without GDP adjustment.

The question raised at this point is: Is really SRISK a good measure of Systemic Risk? Brownlees and Engle (2012) show that SRISK significantly explains the cross-sectional variation of Fed capital injections. Thus, SRISK seems to be connected with the HLA requirement. To backtest this idea, the value of the HLA requirement and the amount of the SRISK have to be compared. The updated list of G-SIBs published by the FSB (2012) is based on 2011 year-end data and Deutsche Bank appears in the first bucket whereas Crédit Agricole is printed in the fourth bucket. At this date and according to Table 1.2, the Deutsche Bank's amount of SRISK^E is equal to 157,718 million euros which puts this bank on top. The third eurozone bank according to SRISK^D and SRISK^E is Crédit Agricole and the amount of the latter is equal to 129,985 million euros. In the first bucket the magnitude of the HLA requirement corresponds to 2.5% of the Risk-Weighted Assets (RWA), while this percentage is fixed at 1% for the fourth bucket. The RWA of Deutsche Bank at the end of 2011 was equal to 381 billion euros leading to a HLA requirement of 9.525 (2.5%×381) billion euros, and the HLA of Crédit Agricole was equal to 3.337 (1%×333.7) billion euros due to a RWA of 333.7 billion euros on December 30, 2011. While RWA amount are above SRISK values, the HLA requirement corresponds to 6.04% and 2.57% of the SRISK value for Deutsche Bank and Crédit Agricole, respectively. Thus, SRISK^E overestimated the amount of HLA which is specific to the systemic risk component whereas SRISK captures the capital shortfall of a given firm when a global financial crisis happens. Then, SRISK is not only composed of the additional risk due to the systemic risk component, a market risk component is also included. This analysis should be extended to econometrically study the link between the HLA requirement and the SRISK. Compared to the ΔCoVaR, the SRISK is expressed as an amount of money which is easily comparable between banks but also for a given bank when comparing different SRISKs. Indeed, when we compute SRISK based on the choice of the system, the localization and the magnitude of the systemic event is modified.

As a consequence, SRISK$^{D/E}$ values are different and 35 out of 42 of the banks have SRISK^D greater than their SRISK^E, highlighting the requirement of additional capital buffer for these 35 banks when they are jointly identified as D- and E-SIB. By how much should a D-SIB increase its Tier one capital to satisfy the regulation? If we do not take into account the SRISK overestimation of the HLA, the difference expressed in million euros should exactly produce this additional amount. Table 1.3 reports the shortage amount of HLA (Value), the domestic ranking (Rank^D) and the eurozone ranking (Rank^E) of all banks based on the difference between SRISK^D and SRISK^E on December 31, 2011. Assuming that all banks are classified as D- and E-SIB, the higher of either D-SIB or E-SIB HLA has to be imposed. In this case, the higher of either SRISK^D or SRISK^E is required and the difference between the two represent the shortage of HLA (when the difference is positive) because we set ex ante the accurate amount of HLA at the eurozone level, as the BCBS want to do with their top-down approach. At the end of 2011, 35 out of 42 banks had a shortage of HLA. In other words, if banks are jointly identified as D and E-SIBs it means that the BCO Santander is undercapitalized by 965 million euros and the National Bank of Greece is undercapitalized by 254 million euros, whereas the Deutsche Bank is well capitalized because the difference is negative (we assume that banks already own the SRISK^E amount).

The shortage of HLA defined as the difference between SRISK^D and SRISK^E has the potential to identify D-SIB and so to be more in line with the bottom-up approach. The higher this shortage is, the larger is the bankruptcy of the bank at the domestic level because its SRISK^E amount is not sufficient to internalize all its negative externalities. Then, ranking banks based on this difference enables to identify banks which may be exclusively D-SIBs, when the shortage is highly positive, and also banks which may be exclusively E-SIBs, when the shortage is highly negative. Table 1.3 shows that Ranks$^{D/E}$ are not identical compared to those from Table 1.2. Thus, with the Rank^D ranking, we can identify which bank is the most domestically risky in a given country. In France, Société Générale is the riskiest whereas according to SRISK^D this bank is behind Crédit Agricole and BNP Paribas.

Once again we would like to backtest this shortage of HLA. Table 1.4 reports the sum of this shortage per country at 3 different dates. We set to 0 the amount when the difference between SRISK^D and SRISK^E is negative because we assume that banks meet the SRISK^E amount. At the end of the sample, Spain and Italy are the two countries with the higher amount of total shortage, 2.235 million and 2.101 million respectively, whereas Belgium and Germany have no shortage. This highlight emphasizes the Spanish and Italian distress during the year 2011 even if these sums were below those at the end of 2009. Germany's results show that its banks are well capitalized and no need of capital injection is required. Belgium banks were already recapitalized at this date and explains the 0 value. This table also shows that the domestic impact of these banks evolves over time which is a good property. Indeed, the Greek shortage reached its peak of 2.811 million euros in this table on December 31, 2009 during the sovereign debt crisis and declined to 349 million euros on December 30, 2011. This result captures the bailout of the Greek economy, which started in 2010.

Table 1.3 Shortage of HLA Rankings per country and over the eurozone

December 30, 2011			
Bank's Name	SRISK^D - SRISK^E		
	Value	Rank^D	Rank^E
Austria			
ERSTE GROUP BANK	407	1	5
RAIFFEISEN BANK INTERNATIONAL	223	2	7
OBERBANK AG	0	3	35
Belgium			
DEXIA	-21	2	38
KBC GRP	-8	1	37
Germany			
DEUTSCHE BANK	-236	3	42
COMMERZBANK	-153	2	41
DEUTSCHE POSTBANK	-87	1	40
Spain			
BCO SANTANDER	965	1	1
BCO BILBAO VIZCAYA ARGENTARIA	800	2	3
BANKIA	110	5	12
CAIXABANK	78	6	17
BCO POPULAR ESPANOL	113	4	11
BCO SABADELL	142	3	9
BANCA CIVICA	-33	8	39
BANKINTER	28	7	25
Finland			
POHJOLA BANK	6	1	34
France			
BNP PARIBAS	26	2	26
CREDIT AGRICOLE	22	3	28
GRP SOCIETE GENERALE	49	1	19
NATIXIS	21	4	29
Greece			
NATIONAL BANK OF GREECE	254	1	6
EFG EUROBANK ERGASIAS	37	3	24
ALPHA BANK	41	2	21
PIRAEUS BANK	7	3	33
BANK OF ATTICA	10	4	32
Ireland			
BANK OF IRELAND	140	1	10
Italy			
UNICREDIT	707	2	4
INTESA SANPAOLO	906	1	2
BCA MONTE DEI PASCHI DI SIENA	107	3	13
BCO POPOLARE	97	4	14
UBI BCA	56	6	18
BCA POPOLARE EMILIA ROMAGNA	42	7	20
BCA POPOLARE DI MILANO	13	11	31
BCA CARIGE	85	5	16
CREDITO EMILIANO	38	8	22
CREDITO VALTELLINESE	13	10	30
BCA POPOLARE DI SONDRIO	38	9	23
CREDITO BERGAMASCO	-4	12	36
Portugal			
BCO COMERCIAL PORTUGUES	96	2	15
BCO ESPIRITO SANTO	209	1	8
BCO BPI	26	3	27

Notes: This table displays the bank's name in the first column, the second column is divided in three small columns with results based on SRISK^D - SRISK^E values. The small column on the left reports SRISK^D - SRISK^E figures in million euros, the middle one discloses the rank of the bank in its country whereas the right column flags the eurozone rank of the bank (number 1 corresponds to the riskiest bank). Rankings are dated from December 30, 2011.

Table 1.4 Shortage of Higher Loss Absorbency per country

Country	September 30, 2008	December 31, 2009	December 30, 2011
Austria	96	708	630
Belgium	0	180	0
Germany	0	0	0
Spain	3,313	3,900	2,235
Finland	0	3	6
France	871	556	119
Greece	1,852	2,811	349
Ireland	93	111	140
Italy	1,260	2,729	2,101
Portugal	1,108	901	331

Notes: This table displays the country's name in the first column, the second, third and fourth column report the shortage of HLA in million euros whether all banks in the country are considered as D- and E-SIB at the same time on September 30, 2008, December 31, 2009 and December 30, 2011, respectively.

Table 1.5 reports the amount (Value), the domestic ranking (Rank^D) and the eurozone ranking (Rank^E) of all banks according to the ΔCoVaR^D and ΔCoVaR^E on December 31, 2011. Domestic rankings are almost the same even though some discrepancies are observed especially for Italy, Spain and Greece, whatever the system considered. Although both ΔCoVaRs produce approximately the same ranking of D-SIBs, the ΔCoVaR^D should be preferred because the domestic system in each country is more suitable to rank banks at the domestic level. The importance (weight) of a domestic bank is better captured inside its domestic index than through an European index. Eurozone ranking derived from the domestic and the eurozone systems are completely different. For instance, the National Bank of Greece is the 14th largest E-SIB, according to the national market, but only the 31st E-SIB when we use the eurozone index. Results are similar for all Greek banks, their ΔCoVaR^D are twice as much than their ΔCoVaR^E. This accentuated the great distress of the Greek economy at the end of 2011, and emphasizes also the fact that this national system was not the most important in the eurozone with regard to its size captured by the relative GDP (relative GDP less than 3%). In contrast, Spain (relative GDP greater than 10%) and Italy (relative GDP greater than 15%) are the two countries which can significantly destabilize the eurozone, especially Spain with the ΔCoVaR^E of its G-SIBs banks like Santander and Banco Bilbao Vizcaya Argentaria being greater than their ΔCoVaR^D. In other words, the systemic contribution of these banks is larger in the eurozone than in their home country. We observe the same phenomena for French, German and Belgium banks. To sum up, global rankings based on the ΔCoVaR^D have no value as long as this eurozone ranking puts on top D-SIBs (not all, as we can see for Bankia which is in the bottom of both lists) belonging to a domestic system in distress on a particular date. Furthermore, we observe that even after the nationalization of Dexia,

Table 1.5 ΔCoVaR Systemic Risk Rankings per country and over the eurozone

December 30, 2011						
Bank's Name	ΔCoVaR^D			ΔCoVaR^E		
	Value	Rank^D	Rank^E	Value	Rank^D	Rank^E
Austria						
ERSTE GROUP BANK	1.58	1	24	1.33	1	19
RAIFFEISEN BANK INTERNATIONAL	1.48	2	29	1.26	2	20
OBERBANK AG	0.12	3	42	0.12	3	42
Belgium						
DEXIA	0.74	2	39	1.18	1	25
KBC GRP	0.75	1	38	1.07	2	30
Germany						
DEUTSCHE BANK	2.03	1	10	1.88	1	5
COMMERZBANK	1.50	2	27	1.40	2	18
DEUTSCHE POSTBANK	0.63	3	41	0.58	3	39
Spain						
BCO SANTANDER	2.51	1	3	2.07	1	1
BCO BILBAO VIZCAYA ARGENTARIA	2.46	2	4	2.02	2	2
BANKIA	1.07	8	35	0.88	8	36
CAIXABANK	1.75	5	19	1.54	4	12
BCO POPULAR ESPANOL	2.18	3	9	1.79	3	7
BCO SABADELL	1.25	7	30	0.99	7	32
BANCA CIVICA	1.58	6	25	1.44	6	16
BANKINTER	1.79	4	16	1.45	5	15
Finland						
POHJOLA BANK	2.42	1	5	1.82	1	6
France						
BNP PARIBAS	2.01	1	11	1.92	1	3
CREDIT AGRICOLE	1.85	3	15	1.75	3	8
GRP SOCIETE GENERALE	1.99	2	12	1.90	2	4
NATIXIS	1.64	4	23	1.55	4	11
Greece						
NATIONAL BANK OF GREECE	1.90	1	14	1.04	1	31
EFG EUROBANK ERGASIAS	1.52	3	26	0.81	4	38
ALPHA BANK	1.65	2	22	0.91	2	33
PIRAEUS BANK	1.15	4	32	0.90	3	34
BANK OF ATTICA	1.01	5	37	0.43	5	41
Ireland						
BANK OF IRELAND	1.09	1	34	1.20	1	22
Italy						
UNICREDIT	2.63	2	2	1.56	2	10
INTESA SANPAOLO	2.76	1	1	1.68	1	9
BCA MONTE DEI PASCHI DI SIENA	2.27	3	7	1.45	4	14
BCO POPOLARE	2.28	4	6	1.43	5	17
UBI BCA	2.21	5	8	1.51	3	13
BCA POPOLARE EMILIA ROMAGNA	1.75	8	18	1.15	9	27
BCA POPOLARE DI MILANO	1.75	7	17	1.18	7	24
BCA CARIGE	1.65	10	21	1.17	8	26
CREDITO EMILIANO	1.99	6	13	1.24	6	21
CREDITO VALTELLINESE	1.67	9	20	1.14	10	28
BCA POPOLARE DI SONDRIO	1.49	11	28	1.08	11	29
CREDITO BERGAMASCO	0.66	12	40	0.53	12	40
Portugal						
BCO COMERCIAL PORTUGUES	1.10	2	33	0.88	3	37
BCO ESPIRITO SANTO	1.04	3	36	0.89	2	35
BCO BPI	1.25	1	31	1.20	1	23

Notes: This table displays the bank's name in the first column, the second and third column are divided in three small columns with results based on ΔCoVaR^D and ΔCoVaR^E values, respectively. The small column on the left reports ΔCoVaR figures in percentage, the middle one discloses the rank of the bank in its country whereas the right column flags the eurozone rank of the bank (number 1 corresponds to the riskiest bank). Rankings are dated from December 30, 2011.

this bank is considered the riskiest Belgian bank based on ΔCoVaR^E, but not on ΔCoVaR^D. Those results show that ΔCoVaR is extremely sensitive to the choice of the system and highlights that large banks, such as Deutsche Bank, Santander, BBVA, BNP Paribas, Société Générale and Unicredit are more affected by an eurozone shock compared to the others. A theoretical argument explains these results: rank^E from ΔCoVaR^D is not useful because the γ_{it}^D coefficients corresponding to the linear projection coefficient of a domestic market return on the bank i return cannot be compared. In this case, the dependent variable is the same only at the domestic level (rank^D) whereas to rank at the European level (rank^E) based on ΔCoVaR^D, we assume that the 10 domestic market returns are comparable, which is a strong assumption. This comment is no longer verified when we use ΔCoVaR^E, Rank^D do not produce additional information compared to Rank^E when we observe the country-per-country ranking.

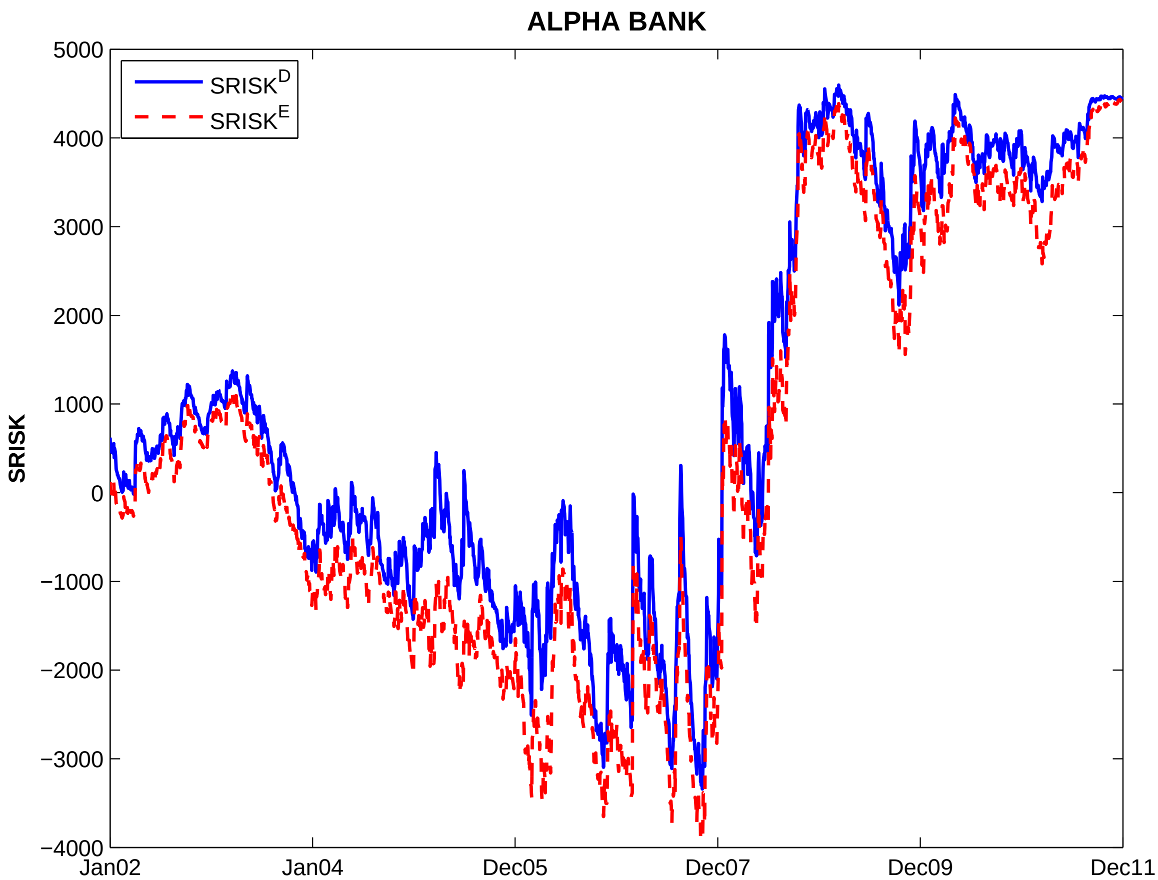
Whatever the system used, SRISKs$^{D/E}$ produce similar rankings at domestic and eurozone levels, but the difference between SRISK^D and SRISK^E can identify D-SIB which are not E-SIB and conversely. In contrast, ΔCoVaR leads to two different rankings, and ΔCoVaR^D should be applied to identify D-SIBs as well as the ΔCoVaR^E to look for E-SIBs.

1.4.3 Time series

The time series analysis of these measures confirms our previous cross-sectional findings and emphasizes the dynamics of these measures to evaluate the systemic contribution of banks over time. Individual plots display results of Alpha Bank but another bank could be used to illustrate our purposes.

Before focusing on Alpha Bank, let's generalize the analysis with some descriptive statistics about the evolution through time of the ranking. For each measure, we compute the Kendall rank-order correlation coefficient between the European systemic risk ranking obtained at time t and the one obtained at time $t-1$. The average correlations are 98.4% for SRISK^D, 98.4% for SRISK^E, 93.5% for ΔCoVaR^D, and 94.7% for ΔCoVaR^E, and are always statistically significant. Thus, rankings are stable through time and the same fact can be observed for the rankings based on the difference between SRISK^D and SRISK^E, and on the MES. We also evaluate the stability of the systemic ranking obtained at time t between the European ranking from SRISK^D and SRISK^E on the one hand, and from ΔCoVaR^D and ΔCoVaR^E on the other hand. The average of the Kendall rank-order correlation coefficient is 95.8% for the SRISK and 49.2% for the ΔCoVaR. This coefficient is statistically significant over time for the SRISK emphasizing the predominant effect of the non-MES component in the ranking based on SRISK. The Kendall rank-order correlation is sometimes non-significant for the ΔCoVaR especially during the sovereign-debt crisis in 2010-2012. This result highlights the sensitivity of the ΔCoVaR to the choice of the system and shows that ΔCoVaR^D gives additional information which may be useful at the domestic level. However, ranking banks at the European level based on ΔCoVaR^D does not make sense because we sort conditional quantile from different domestic market index, i.e. various conditional domestic market indexes distribution. This is the main difference between the ΔCoVaR and the MES (SRISK) because MES involves comparing the distribution of a firm's stock return, conditional on a market crisis. The average Kendall rank-order correlation between the European ranking based on MES^D and MES^E is equal to 74.3%, and this coefficient is always significant.

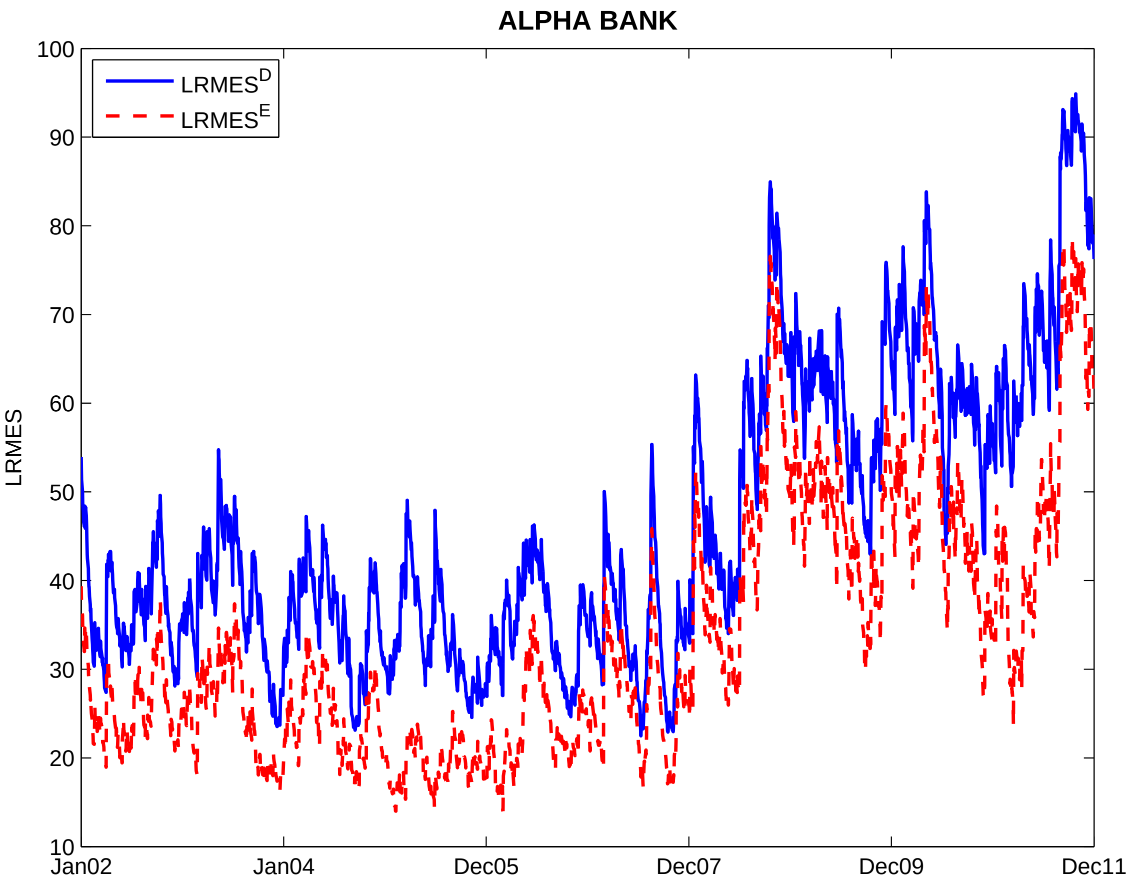
Figure 1.2 SRISK of Alpha Bank



Notes: This figure displays the SRISK^D (blue solid line) and the SRISK^E (red dashed line) of Alpha Bank in million of euros. The estimation period is from 02/01/2002 to 12/30/2011.

Figure 1.2 displays the evolution of both SRISK^D and SRISK^E for Alpha Bank from January 2, 2002 and December 30, 2011. The gap between domestic and eurozone SRISK is not constant over time although the coefficient of correlation between these two systemic risk measures is equal to 0.99. Moreover, when both markets are in crisis, curves are closer. As predicted, for this bank SRISK^D is above the SRISK^E because the domestic MES is above the eurozone MES, as shown by Figure 1.3 where dynamics of the $\text{LRMESs}^{D/E}$ are plotted. The correlation coefficient reported in Figure 1.1 is lower at a global level for a technical reason. Indeed, the weighting factor of this bank used to construct the eurozone index is lower than the one used to build the domestic index. The correlation coefficient is the main driver of the LRMES and explains why the LRMES^D is above the LRMES^E. Thus, the sensitivity of Alpha Bank to a domestic equity shock is greater than its sensitivity to an eurozone equity shock. In average over the period, the difference between SRISK^D and SRISK^E is equal to 544 million euros but the difference is twice as much in average for National Bank of Greece and EFG Eurobank Ergasias.

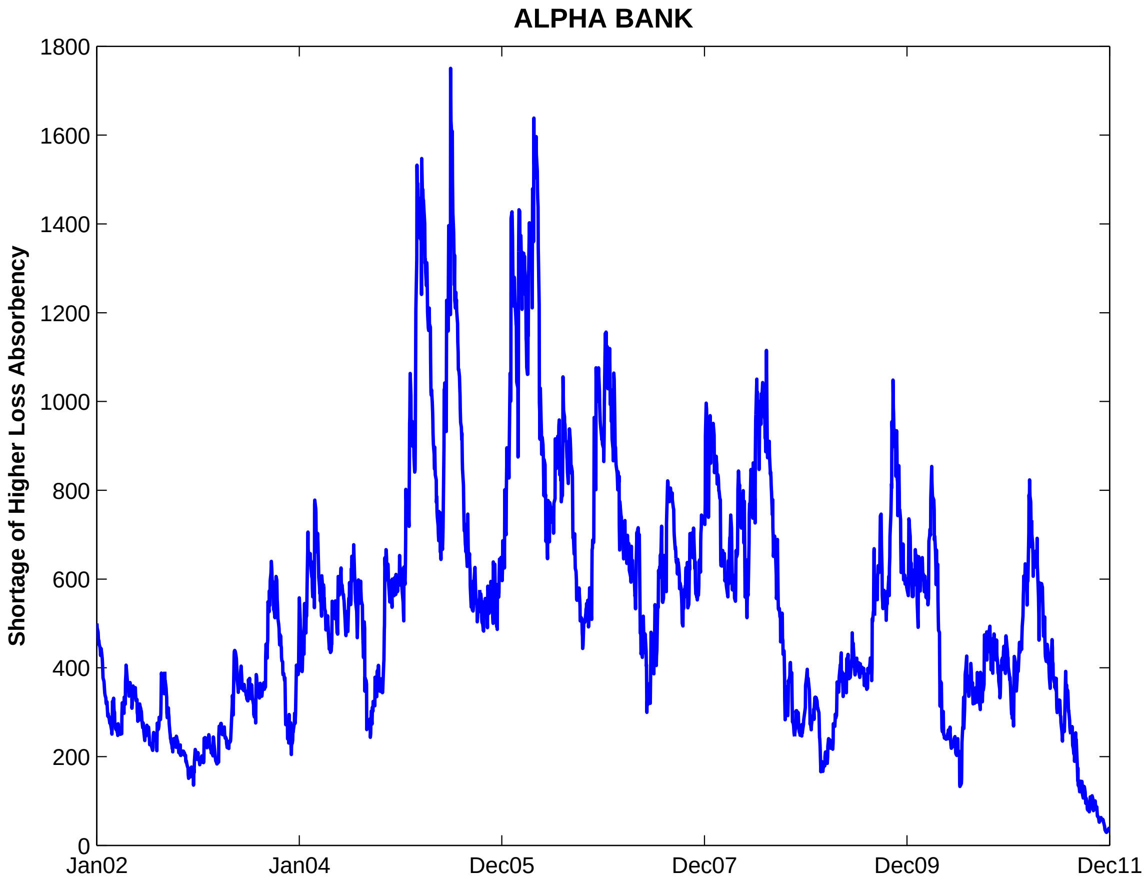
Figure 1.3 LRMES of Alpha Bank



Notes: This figure displays the LRMES^D and the LRMES^E of Alpha Bank return with its domestic index (blue solid line) and with its eurozone index (red dashed line) in percentage. The estimation period is from 01/02/2002 to 12/30/2011.

As observed in Figure 1.2, if a bank is simultaneously identified as a D- and E-SIB then the higher of either D-SIB or E-SIB HLA requirements has to be met. Figure 1.4 displays this shortage of HLA for Alpha Bank over the period. The dynamics of the shortage show that this amount relies on the firm's characteristics and economic conditions. The amount of this shortage for Alpha Bank reached its top around 1,800 million euros in 2005 and was at its lowest at the end of 2011, around 41 million.

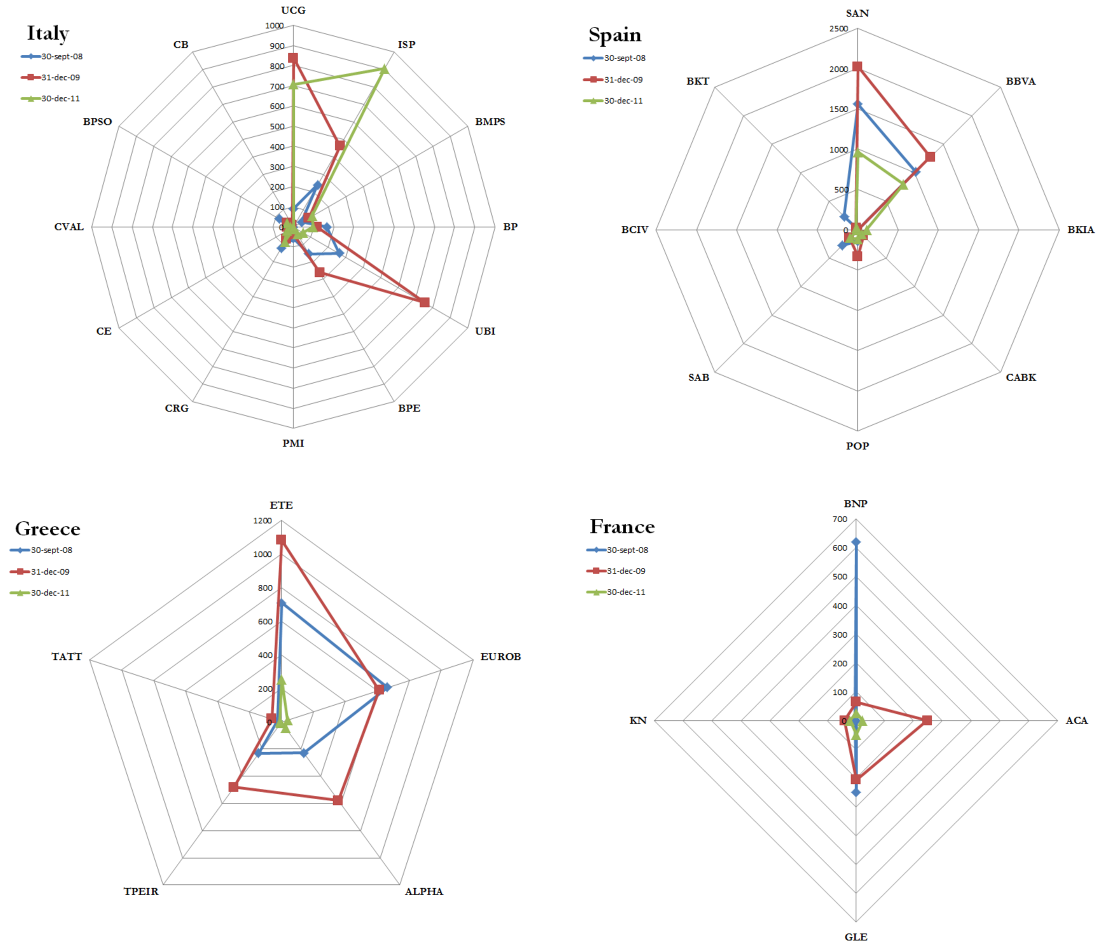
Figure 1.4 Shortage of HLA of Alpha Bank



Notes: This figure displays the shortage of HLA (blue solid line) of Alpha Bank in million of euros whether this bank is considered as D- and E-SIB at the same time. The estimation period is from 02/01/2002 to 12/30/2011.

Figure 1.5 displays 4 radar plots where the breakdown by banks of the total shortage of HLA for a given country is realized at 3 different dates. In Italy, strong change appeared over time while Unicredit and Intesa Sanpaolo remains the main contributors but UBI BCA has been removed from this list of large contributors since 2009. In Spain, Santander and BBVA remain the main contributors to the total shortage over time. It means that their domestic effect is high and has to be internalized. In other words, their amount of capital requirement is undervalued due to their domestic impact. In Greece, National Bank of Greece and EFG Eurobank Ergasias as well as Alpha Bank and Piraeus Bank on December 31, 2009 were major systemic risk contributors. However, as in Table 1.4, their contribution has significantly decreased at the end of the period. In France, BNP Paribas was on top on September 30, 2008 but was replaced by Crédit Agricole on December 31, 2009. At year-end 2011 their contributions were close to 0.

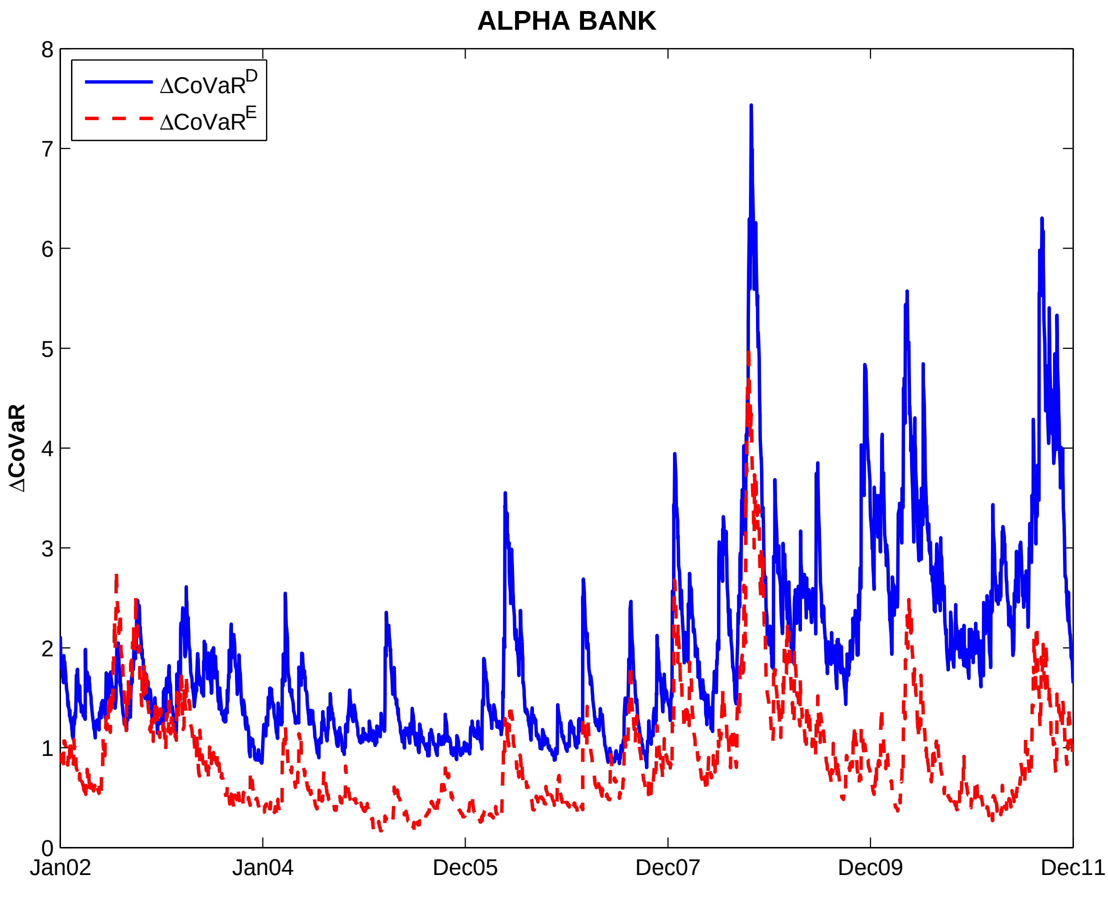
Figure 1.5 Radar plots of shortage of HLA per country



Notes: This figure displays 4 radar plots with three snapshots each, of the breakdown by banks of a particular country of the shortage of Higher Loss Absorbency (expressed in million euros) when all banks are considered as D- and E-SIB at the same time. In the top left-hand corner, there is the Italian radar plot; in the top right-hand corner, the Spanish radar plot; in the bottom left-hand corner, the Greek radar plot; and in the bottom right-hand corner, the French radar plot. Tickers from Appendix 1.6.5 are used to represent the country's banks. These snapshots are dated from September 30, 2008 (blue solid line), December 31, 2009 (red solid line) and December 30, 2011 (green solid line).

Figure 1.6 displays the evolution of both ΔCoVaR^D and ΔCoVaR^E for Alpha Bank from January 2, 2002 and December 30, 2011. The correlation coefficient between the domestic ΔCoVaR^D and the eurozone ΔCoVaR^E is equal to 0.65. This coefficient is low due to the choice of the estimation method which allows to produce a time-varying proportional coefficient between the ΔCoVaR and VaR. Indeed, if we estimate ΔCoVaR with a quantile regression with or without macro-variables, we have a perfect correlation between both ΔCoVaRs. In this case, the time series dynamics are the same for the both national and the eurozone systems. However, it does not mean that the ranking is the same because the magnitude between these curves can be large. The ΔCoVaR is extremely sensitive to the estimation method. Moreover, contrary to the SRISK (MES) approach, in the ΔCoVaR approach, the localization of the system of reference has an impact only on the $\gamma^{D/E}$ coefficient and not on the magnitude of the systemic event which corresponds in both cases to the VaR of the financial institution. With this figure, we show that the ΔCoVaR^E can be above the ΔCoVaR^D due to a higher interconnection between banks in the eurozone than in their own market. At the end of the period, we observe that the ΔCoVaR^D remains high whereas the ΔCoVaR^E becomes lower and less volatile. The systemic contribution of Alpha Bank is then higher within its domestic market than at the eurozone level because the return correlation with the global market decreases, as we can see in Figure 1.1.

Figure 1.6 ΔCoVaR of Alpha Bank



Notes: This figure displays the ΔCoVaR^D (blue solid line) and the ΔCoVaR^E (red dashed line) of Alpha Bank in percentage. The estimation period is from 01/02/2002 to 12/30/2011.

This empirical part shows the evidence that the choice of the system is a key factor in measuring systemic risk contribution with the SRISK and the ΔCoVaR. We also point out that the correlation between the financial institution and its system is the only mathematical tool to take into account this change in the system aggregate level. Jiang (2012) argues that the dependence among bank and market returns is nonlinear and that copula approaches need to be used to capture this dependence, yet even with this methodology the level-playing field is crucial.

1.5 Conclusion

The identification of the systemically important banks is a high-priority task for regulators around the world even if identifying and measuring systemic risk is a challenge (Hansen, 2014). While most research focuses on firms that are globally systemic (G-SIBs), this paper applies market-based systemic risk measures in a domestic and eurozone framework in order to identify and regulate D-SIBs (BCBS, 2012), and study their behavior when the system of reference changes. Simple quantification of systemic risk based on market data may be too restrictive and their model unrealistic. However, these SRMs are powerful tools to understand and validate the discretion of the regulators' action on systemic risk policy. At the European level, home and host authorities, both being the domestic supervisors of a given bank with its subsidiaries, conduct their supervision after the identification of E-SIBs. Any additional requirements and other policy measures to internalize the risk posed by a D-SIB should be clearly documented by the national authorities and follow the principles stated by the BCBS, i.e. the Global/European regulator. Following this guideline, we have adjusted market-based SRMs used to identify G-SIBs to investigate the systemic risk contribution of a given bank at the domestic level and extract specific additional policy for D-SIBs as required by the BCBS.

Our main conclusions are the following. First, the SRISK methodology produces identical rankings regardless of the reference system used because SRISK-based ranking is mainly sensitive to the total amount of liabilities of the bank, which does not depend on the size of the system. Thus, this measure fails to identify D-SIBs but the difference between SRISK^D and SRISK^E, in which the impact of the liabilities disappears, allows to identify D-SIBs, as well as the most systemic countries within the eurozone. This property of the difference between SRISK^D and SRISK^E is due to the fact that we capture the spread between the degree of interconnection of the bank with the European system and the domestic system through the LRMES. Moreover, this difference captures the shortage of HLA that a given bank may have when this financial institution is jointly identified as E- and D-SIB. Second, our findings also indicate that in the ΔCoVaR methodology a bank could be identified as E-SIBs but not as D-SIBs, and conversely. In this measure, for a given bank, the systemic event is not specific to the system of reference and its magnitude remains the same. However, the dependent variable of the linear projection of a particular market return on the bank return is not the same. To overcome this issue and thus to rank banks when the same dependent variable is used, we apply the ΔCoVaR^D to identify D-SIBs and the ΔCoVaR^E for E-SIBs.

This paper highlights the lack of specific factors directly connected to the system in which the bank is operating. A network approach, already used to deal with systemic risk (Eisenberg and Noe, 2001; Demange, 2011), seems to be an attractive approach to capture all the characteristics of the system but it requires more data to be collected. Thus, producing an accurate domestic systemic risk measure based on a network approach should be a priority.

1.6 Appendices

1.6.1 Appendix: The Framework

We consider a simple bivariate model where the demeaned market return at time t, r_{mt}, and the demeaned firm return of a given bank i at time t, r_{it}, are expressed as:

$$r_{mt} = \sigma_{mt}\, \varepsilon_{mt} \;, \tag{1.10}$$

$$r_{it} = \sigma_{it}\, \varepsilon_{it} \;, \tag{1.11}$$

where σ_{it} and σ_{mt} are the conditional standard deviations whereas ε_{it} and ε_{mt} are the conditional standardized residuals. The conditional correlation between market and bank returns ρ_{it} is equal to:

$$\rho_{it} = \frac{\sigma_{imt}}{\sigma_{it}\;\sigma_{mt}} \Leftrightarrow \rho_{it}\;\sigma_{it} = \frac{\sigma_{imt}}{\sigma_{mt}} \;, \tag{1.12}$$

where σ_{imt} is the conditional covariance. The conditional systematic risk of a given bank β_{it} is defined as follows:

$$\beta_{it} = \frac{\sigma_{imt}}{\sigma_{mt}\;\sigma_{mt}} = \frac{\sigma_{imt}}{\sigma_{mt}^2} \;. \tag{1.13}$$

According to the market model, the bank return is:

$$\begin{aligned} r_{it} &= \beta_{it}\; r_{mt} + \eta_{it} \\ &= \frac{\sigma_{imt}}{\sigma_{mt}^2}\; \sigma_{mt}\; \varepsilon_{mt} + \eta_{it} \\ &= \frac{\sigma_{imt}}{\sigma_{mt}}\; \varepsilon_{mt} + \eta_{it} \\ &= \rho_{it}\; \sigma_{it}\; \varepsilon_{mt} + \eta_{it} \\ &= \rho_{it}\; \sigma_{it}\; \varepsilon_{mt} + \sigma_{\eta_{it}}\; \xi_{it} \;. \end{aligned} \tag{1.14}$$

Then we compute the bank variance:

$$\mathbb{V}(r_{it}) = \sigma_{it}^2 = \sigma_{it}^2\; \rho_{it}^2 + \sigma_{\eta_{it}}^2 \;. \tag{1.15}$$

The first part of Eq. (1.15) corresponds to the systematic risk whereas the second part is the idiosyncratic risk. Hence, we extract the idiosyncratic risk when we subtract the systematic risk from the total risk of bank i as shown in the following equation:

$$\Rightarrow \quad \sigma_{\eta_{it}}^2 = \sigma_{it}^2 \left[1 - \rho_{it}^2\right] \tag{1.16}$$

$$\Rightarrow \quad \sigma_{\eta_{it}} = \sigma_{it}\sqrt{1 - \rho_{it}^2} \;. \tag{1.17}$$

Thus the bank return becomes:

$$\begin{aligned} r_{it} &= \rho_{it}\; \sigma_{it}\; \varepsilon_{mt} + \sigma_{it}\sqrt{1-\rho_{it}^2}\; \xi_{it} \\ &= \sigma_{it} \left(\rho_{it}\; \varepsilon_{mt} + \sqrt{1-\rho_{it}^2}\; \xi_{it}\right) \;. \end{aligned} \tag{1.18}$$

Finally, we obtain the exact same framework as Brownlees and Engle (2012):

$$r_{mt} = \sigma_{mt}\, \varepsilon_{mt} \,, \tag{1.19}$$

$$r_{it} = \sigma_{it}\, \rho_{it}\, \varepsilon_{mt} + \sigma_{it} \sqrt{1-\rho_{it}^2}\, \xi_{it} \,, \tag{1.20}$$

$$(\varepsilon_{mt},\, \xi_{it}) \sim D \,, \tag{1.21}$$

where $r_{mt} \perp \xi_{it}$, the process $\nu_t = (\varepsilon_{mt}, \xi_{it})'$ is *i.i.d.* over time but not in cross-section, and satisfies $\mathbb{E}(\nu_t) = 0$ and $\mathbb{E}(\nu_t \nu_t') = I_2$, a two-by-two identity matrix, and D is a bivariate distribution of these standardized innovations, which is assumed to be unknown.

1.6.2 Appendix: The MES Formula

According to Appendix A and the definition of the expected shortfall of a *particular market* return:

$$ES_{mt}(\alpha) = \mathbb{E}_{t-1}\Big(r_{mt} \mid r_{mt} < C\Big) = \sum_{i=1}^{N} w_{it}^{S}\ \mathbb{E}_{t-1}\Big(r_{it} \mid r_{mt} < C\Big)\ , \tag{1.22}$$

where N firms form the *particular system*, noted S, and r_{it} denotes the return of firm i at time t. Similarly, the market return of this *particular system* is the value-weighted average of all firm returns including in this *particular system*, $r_{mt} = \sum_{i=1}^{N} w_{it}^{S}\ r_{it}$, where w_{it}^{S} denotes the relative market capitalization of firm i within this *particular system*.

According to Scaillet (2004), we have the following expression for the MES of a given specific event C on the market return for a level of risk α can be expressed as:

$$\begin{aligned} MES_{it}(\alpha) &= \frac{\partial ES_{mt}(C)}{\partial w_{it}^{S}} = \mathbb{E}_{t-1}\Big(r_{it} \mid r_{mt} < C\Big) \\ &= \sigma_{it}\ \mathbb{E}_{t-1}\left(\varepsilon_{it} \mid \varepsilon_{mt} < \frac{C}{\sigma_{mt}}\right) \\ &= \sigma_{it}\ \mathbb{E}_{t-1}\left(\rho_{it}\ \varepsilon_{mt} + \sqrt{1-\rho_{it}^{2}}\ \xi_{it} \mid \varepsilon_{mt} < \frac{C}{\sigma_{mt}}\right)\ . \end{aligned} \tag{1.23}$$

And we have:

$$\begin{aligned} MES_{it}(\alpha) &= \sigma_{it}\ \rho_{it}\ \mathbb{E}_{t-1}\left(\varepsilon_{mt} \mid \varepsilon_{mt} < \frac{C}{\sigma_{mt}}\right) \\ &\quad + \sigma_{it}\ \sqrt{1-\rho_{it}^{2}}\ \mathbb{E}_{t-1}\left(\xi_{it} \mid \varepsilon_{mt} < \frac{C}{\sigma_{mt}}\right)\ . \end{aligned} \tag{1.24}$$

In this application, $C = VaR_{mt}(\alpha)$, which is the Value-at-Risk (at the $\alpha = 5\%$ level of risk) of the *reference market* and its associated expected shortfall is given by:

$$ES_{mt}(\alpha) = \mathbb{E}_{t-1}\Big(r_{mt} \mid r_{mt} < VaR_{mt}(\alpha)\Big)\ , \tag{1.25}$$

and the MES is equal to:

$$\begin{aligned} MES_{it}(\alpha) &= \sigma_{it}\ \rho_{it}\ \mathbb{E}_{t-1}\left(\varepsilon_{mt} \mid \varepsilon_{mt} < \frac{VaR_{mt}(\alpha)}{\sigma_{mt}}\right) \\ &\quad + \sigma_{it}\ \sqrt{1-\rho_{it}^{2}}\ \mathbb{E}_{t-1}\left(\xi_{it} \mid \varepsilon_{mt} < \frac{VaR_{mt}(\alpha)}{\sigma_{mt}}\right)\ . \end{aligned} \tag{1.26}$$

Caporin and de Magistris (2012) show that Eq. (1.26) only holds as an approximation with log-returns.

1.6.3 Appendix: SRISK Formula

Engle, Jondeau and Rockinger (2014) in their paper Systemic Risk in Europe define the capital shortfall of a given bank i as follow:

$$\begin{aligned}
CS_{i,t:t+T} &= \mathbb{E}_{t-1}\Big[\, k\ A_{i,t+T} - W_{i,t+T} \big|\, Crisis_{t:t+T}\Big] \\
&= \mathbb{E}_{t-1}\Big[\, k\ (D_{i,t+T} + W_{i,t+T}) - W_{i,t+T} \big|\, Crisis_{t:t+T}\Big] \\
&= \mathbb{E}_{t-1}\Big[\, k\ D_{i,t+T} - (1-k)\ W_{i,t+T} \big|\, Crisis_{t:t+T}\Big]\ , \qquad (1.27)
\end{aligned}$$

where $A_{i,t}$ and $W_{i,t}$ denote the value of the assets and equity of bank i and k is a prudential capital ratio of equity to assets. In the short-run, $D_{i,t+T} = D_{i,t}$ and the financial leverage is defined as $L_{i,t} = A_{i,t}/W_{i,t}$, so that $D_{i,t} = (L_{i,t} - 1)\ W_{i,t}$:

$$CS_{i,t:t+T} = \left(k\ (L_{i,t} - 1) - (1-k)\ \mathbb{E}_{t-1}\left[\frac{W_{i,t+T}}{W_{i,t}}\middle|\, Crisis_{t:t+T}\right]\right) W_{i,t}\ , \qquad (1.28)$$

where

$$\begin{aligned}
\mathbb{E}_{t-1}\left[\frac{W_{i,t+T}}{W_{i,t}}\middle|\, Crisis_{t:t+T}\right] &= 1 + \mathbb{E}_{t-1}\left[\frac{W_{i,t+T}}{W_{i,t}} - 1\middle|\, Crisis_{t:t+T}\right] \\
&= 1 - LRMES_{i,t:t+T}\ , \qquad (1.29)
\end{aligned}$$

and $LRMES_{i,t:t+T} = -\mathbb{E}_{t-1}\left[\frac{W_{i,t+T}}{W_{i,t}} - 1\middle|\, Crisis_{t:t+T}\right]$ which is the long-run marginal expected shortfall of the bank's return in case of a financial crisis event. Eq. (1.28) can be rewritten as:

$$\begin{aligned}
CS_{i,t:t+T} &= \Big[k\ (L_{i,t} - 1) - (1-k)\ (1 - LRMES_{i,t:t+T})\Big]\ W_{i,t} \\
&= k\ D_{i,t}\ - (1-k)\ (1 - LRMES_{i,t:t+T})\ W_{i,t}\ . \qquad (1.30)
\end{aligned}$$

For a worldwide crisis, the systemic event is approximated by a fall of 40% at a time of horizon six months. This decline corresponds to the worst six months market drop over the last decade on the US market (i.e. S&P500). Then LRMES is defined as:

$$LRMES_{i,t:t+T} = -\mathbb{E}_{t-1}\Big(\, R_{i,t:t+T} \big|\, R_{m,t:t+T} \leq -40\%\Big)\ , \qquad (1.31)$$

where $R_{i,t:t+T}$ and $R_{i,t:t+T}$ are cumulative returns defined as:

$$R_{i,t:t+T} = \exp\left(\sum_{j=1}^{T} r_{i,t+j}\right) - 1 \quad \text{and} \quad R_{m,t:t+T} = \exp\left(\sum_{j=1}^{T} r_{m,t+j}\right) - 1\ ,$$

$r_{i,t}$ and $r_{m,t}$ are the log-return of bank i and the log-return of the *particular market index* (as given in Appendix B) respectively, $T = 126$. Then, the LRMES is estimated by:

$$LRMES_{i,t:t+T} = \frac{-1}{\sum_{s=1}^{S} I\left(R^{(s)}_{M,t:t+T} \leq -40\%\right)} \sum_{s=1}^{S} R^{(s)}_{i,t:t+T} \times\ I\left(R^{(s)}_{m,t:t+T} \leq -40\%\right)\ . \qquad (1.32)$$

where $I(x) = 1$ if x is true and 0 otherwise. Empirically, this simulation is time consuming and even if it leads to accurate estimation of the long-run marginal expected shortfall,

some cautions have to be apply after the steps of simulation to end up with stationary returns and not explosive MES trajectories (Banulescu and Dumitrescu, 2013).
Thus, Acharya, Engle and Richardson (2012) compute the LRMES without simulation. They approximate it by:

$$LRMES_{i,t:t+T} = -\Big(\exp(18 \times MES_{i,t}) - 1\Big) = 1 - \exp(18 \times MES_{i,t}) \ , \tag{1.33}$$

where MES is the one day loss expected if market return is less than -2%. In this paper, this loss is replaced by the daily *market* VaR at the 5% level of risk and so take into account the volatility difference of a *particular market* and end up with $MES_{it}(\alpha)$ (see Appendix B). Then, the generalized formula of the capital shortfall is equal to:

$$CS_{i,t:t+T} = k \ D_{i,t} \ - (1-k) \ \exp\Big(\theta_i \times MES_{i,t}(\alpha)\Big) \ W_{i,t} \ , \tag{1.34}$$

where $\theta_i = \theta = 18$ which is the calibration used by Acharya, Engle and Richardson (2012) for the US stock market. This coefficient is assumed to be constant across banks and through time within a *particular market*. However, this coefficient should be bank-specific as in the simulated way. A specific θ_i coefficient to take into account for the difference in volatility of the market returns across countries for a given bank could be used. This coefficient is defined as followed:

$$\theta_i = \frac{\mathbb{E}_t\Big(R_{i,t:t+T} | \, R_{m,t:t+T} \leq VaR_{m,t:t+T}(\alpha)\Big)}{\mathbb{E}_t\Big(R_{i,t:t+1} | \, R_{m,t:t+1} \leq VaR_{m,t:t+1}(\alpha)\Big)} \ , \tag{1.35}$$

where $VaR_{m,t:t+T}(\alpha)$ is a semi-annual market VaR at the 5% level of risk whereas $VaR_{m,t:t+1}(\alpha)$ is a daily market VaR at the 5% level of risk. However, this methodology leads to very different estimation of θ_i and far from the 18 which is the average value through banks of Eq. (1.35) in the US stock market. To avoid this issue which could lead to inaccurate SRISK results and focus on this assumption later, we also assume that θ_i coefficient is constant over time and the same for all banks to obtain the same MES transformation. Thus, its value is set at 18. To conclude, the systemic contribution of firm i is the positive capital shortfall:

$$\begin{aligned} SRISK_{i,t:t+T} &= \max\Big(0 \ ; CS_{i,t:t+T}\Big) \\ &= \max\Big(0 \ ; k \ D_{i,t} \ - (1-k) \ \exp\Big(\theta \times MES_{i,t}(\alpha)\Big) \ W_{i,t}\Big) \ . \end{aligned} \tag{1.36}$$

The contribution to aggregate SRISK by any bank is also given by:

$$SRISK\%_{i,t:t+T} = \frac{SRISK_{i,t}}{\sum\limits_{j \ \in \ J} SRISK_{j,t}} \ , \tag{1.37}$$

where $J = \{\text{banks with positive SRISK}\}$.

1.6.4 Appendix: The CoVaR Formula

The CoVaR corresponds to the VaR of a *particular market* obtained conditional on some event $\mathbb{C}(r_{it})$ observed for bank i belongs to this *particular system*:

$$\Pr\Big(r_{mt} \leq CoVaR_t^{m|\mathbb{C}(r_{it})} \ \Big| \ \mathbb{C}(r_{it})\Big) = \alpha \ , \tag{1.38}$$

where α is the level of risk of this conditional probability. Given the simple bivariate process describes in Appendix A as:

$$\begin{aligned} r_{mt} &= \sigma_{mt} \ \epsilon_{mt} \ , &(1.39)\\ r_{it} &= \sigma_{it} \ \epsilon_{it} \ , &(1.40)\end{aligned}$$

where $(r_{mt}, r_{it}) \sim D$, D is a bivariate distribution with $\nu_t = (r_{mt}, r_{it})'$ satisfies $\mathbb{E}(\nu_t) = 0$, and $\mathbb{E}(\nu_t \nu_t') = H_t = \begin{pmatrix} \sigma_{mt}^2 & \rho_{it} \ \sigma_{it} \ \sigma_{mt} \\ \rho_{it} \ \sigma_{it} \ \sigma_{mt} & \sigma_{it}^2 \end{pmatrix}$, the conditional variance/covariance matrices. If the conditional mean function of r_{mt} is linear in r_{it}, the first two conditional moments of r_{mt} given $r_{it} = c$ can be expressed by the following:

$$\begin{aligned} \mathbb{E}\Big(r_{mt} \ | \ r_{it} = c\Big) &= \frac{\text{cov}(r_{mt}, r_{it})}{\sigma_{it}^2} \times c \\ &= \frac{\rho_{it} \ \sigma_{it} \ \sigma_{mt}}{\sigma_{it}^2} \times c \\ &= \frac{\rho_{it} \ \sigma_{mt}}{\sigma_{it}} \times c \ , \end{aligned} \tag{1.41}$$

$$\begin{aligned} \mathbb{V}\Big(r_{mt} \ | \ r_{it}\Big) &= \mathbb{V}(r_{mt}) - \Big[1 - \rho_{it}^2\Big] \\ &= \sigma_{mt}^2 \ (1 - \rho_{it}^2) \ . \end{aligned} \tag{1.42}$$

We standardized this *particular market* return and get:

$$\Pr\left(\frac{r_{mt} - \frac{\rho_{it} \ \sigma_{mt}}{\sigma_{it}} \times r_{it}}{\sigma_{mt} \ \sqrt{(1 - \rho_{it}^2)}} \leq \frac{CoVaR_{it}^{m|\mathbb{C}(r_{it})} - \frac{\rho_{it} \ \sigma_{mt}}{\sigma_{it}} \times r_{it}}{\sigma_{mt} \ \sqrt{(1 - \rho_{it}^2)}} \ \middle| \ \mathbb{C}(r_{it})\right) = \alpha \ . \tag{1.43}$$

Thus, when bank i is in distress we have $\mathbb{C}(r_{it}) : r_{it} = VaR_{it}(\alpha)$, Eq. (1.43) is expressed as:

$$CoVaR_{it}^{m|r_{it}=VaR_{it}(\alpha)} = \frac{\rho_{it} \ \sigma_{mt}}{\sigma_{it}} \times VaR_{it}(\alpha) + \left(\sigma_{mt} \ \sqrt{(1 - \rho_{it}^2)}\right) G^{-1}(\alpha) \ , \tag{1.44}$$

where $G(.)$ is the conditional distribution of r_{mt}.

When bank i is just fine, $\mathbb{C}(r_{it}) : r_{it} = Median(r_{it})$, Eq. (1.43) becomes:

$$\begin{aligned} CoVaR_{it}^{m|r_{it}=Median_i} &= \frac{\rho_{it} \ \sigma_{mt}}{\sigma_{it}} \times Median(r_{it}) + \left(\sigma_{mt} \ \sqrt{(1 - \rho_{it}^2)}\right) G^{-1}(\alpha) \\ &= \frac{\rho_{it} \ \sigma_{mt}}{\sigma_{it}} \times VaR_{it}(0.5) + \left(\sigma_{mt} \ \sqrt{(1 - \rho_{it}^2)}\right) G^{-1}(\alpha) \ . \end{aligned} \tag{1.45}$$

Finally, the systemic contribution of a given bank i to the risk of a *particular system* is equal to

$$\begin{aligned}
\Delta CoVaR_{it} &= CoVaR_{it}^{m|r_{it}=VaR_{it}(\alpha)} - CoVaR_{it}^{m|r_{it}=Median(r_{it})} \\
&= \frac{\rho_{it}\ \sigma_{mt}}{\sigma_{it}} \times VaR_{it}(\alpha) + \left(\sigma_{mt}\ \sqrt{(1-\rho_{it}^2)}\right)\ G^{-1}(\alpha) \\
&\quad - \left[\frac{\rho_{it}\ \sigma_{mt}}{\sigma_{it}} \times VaR_{it}(0.5) + \left(\sigma_{mt}\ \sqrt{(1-\rho_{it}^2)}\right)\ G^{-1}(\alpha)\right] \\
\Delta CoVaR_{it} &= \frac{\rho_{it}\ \sigma_{mt}}{\sigma_{it}} \left[VaR_{it}(\alpha) - VaR_{it}(0.5)\right]. \qquad (1.46)
\end{aligned}$$

where the linear projection coefficient of *a particular market* return on the bank return is equal to $\gamma_{it} = \rho_{it}\ \sigma_{mt}\ /\ \sigma_{it}$. When we assume a location-scale distribution for r_{it}, we have $VaR_{it}(\alpha) = \sigma_{it}\ F^{-1}(\alpha)$, with $F(.)$ the marginal distribution of ϵ_{it} (this pdf is symmetric around 0) and $F^{-1}(\alpha)$ is the empirical quantile of the standardized innovations of r_{it}. Thus, the systemic contribution corresponds to $\Delta CoVaR_{it} = \rho_{it}\ \sigma_{mt}\ F^{-1}(\alpha)$.

1.6.5 Appendix: Dataset

Tickers and Company Names per Country

Austria (3)	
EBS	ERSTE GROUP BANK
OBS	OBERBANK AG
RBI	RAIFFEISEN BANK INTERNATIONAL
Belgium (2)	
DEXB	DEXIA
KBC	KBC GRP
Germany (3)	
CBK	COMMERZBANK
DBK	DEUTSCHE BANK
DPB	DEUTSCHE POSTBANK
Spain (8)	
BCIV	BANCA CIVICA
BKIA	BANKIA
BKT	BANKINTER
BBVA	BCO BILBAO VIZCAYA ARGENTARIA
POP	BCO POPULAR ESPANOL
SAB	BCO SABADELL
SAN	BCO SANTANDER
CABK	CAIXABANK
Finland (1)	
POH1S	POHJOLA BANK
France (4)	
BNP	BNP PARIBAS
ACA	CREDIT AGRICOLE
GLE	GRP SOCIETE GENERALE
KN	NATIXIS
Greece (5)	
ALPHA	ALPHA BANK
TATT	BANK OF ATTICA
EUROB	EFG EUROBANK ERGASIAS
ETE	NATIONAL BANK OF GREECE
TPEIR	PIRAEUS BANK
Ireland (1)	
BIR	BANK OF IRELAND
Italy (12)	
CRG	BCA CARIGE
BMPS	BCA MONTE DEI PASCHI DI SIENA
PMI	BCA POPOLARE DI MILANO
BPSO	BCA POPOLARE DI SONDRIO
BPE	BCA POPOLARE EMILIA ROMAGNA
BP	BCO POPOLARE
CB	CREDITO BERGAMASCO
CE	CREDITO EMILIANO
CVAL	CREDITO VALTELLINESE
ISP	INTESA SANPAOLO
UBI	UBI BCA
UCG	UNICREDIT
Portugal (3)	
BPI	BCO BPI
BCP	BCO COMERCIAL PORTUGUES
BES	BCO ESPIRITO SANTO

Chapter 2

A Theoretical and Empirical Comparison of Systemic Risk Measures[23]

We derive several popular systemic risk measures in a common framework and show that they can be expressed as transformations of market risk measures (e.g. beta). We also derive conditions under which the different measures lead to similar rankings of systemically important financial institutions (SIFIs). In an empirical analysis of US financial institutions, we show that (*i*) different systemic risk measures identify different SIFIs and that (*ii*) firm rankings based on systemic risk estimates mirror rankings obtained by sorting firms on market risk or liabilities. One-factor linear models explain most of the variability of the systemic risk estimates, which indicates that systemic risk measures fall short in capturing the multiple facets of systemic risk.

2.1 Introduction

The recent financial crisis has fostered extensive research on systemic risk, either on its definition, measurement, or regulation. Of particular interest is the identification of the financial institutions that contribute the most to the overall risk of the financial system – the so-called Systemically Important Financial Institutions (SIFIs). The Financial Stability Board (2011) defines SIFIs as "financial institutions whose distress or disorderly failure, because of their size, complexity and systemic interconnectedness, would cause significant disruption to the wider financial system and economic activity". As they pose a major threat to the system, regulators and policy makers from around the world have called for tighter supervision, extra capital requirements, and liquidity buffers for SIFIs (Financial Stability Board, 2011).[24]

[23]This chapter is based on Benoit, Colletaz, Hurlin and Pérignon (2014).

[24]For some banks, the benefits of being designated a SIFI outweigh the costs. As put by Douglas Flint, the chairman of HSBC (http://www.guardian.co.uk/business/2011/nov/06/banks-disappointed-not-on-g-sifi-list): "I see it as a label

In practice, there are two ways of measuring the contribution of a given financial institution to the risk of the system. The first approach relies on information on positions and risk exposures. This confidential information is provided by the financial firms to the regulator.[25] The second approach only relies on public market data, such as stock returns, option prices, or CDS spreads, as they are believed to reflect all information about publicly traded firms. Four prominent examples of such measures are the *Marginal Expected Shortfall* (MES) and the *Systemic Expected Shortfall* (SES) of Acharya et al. (2010), the *Systemic Risk Measure* (SRISK) of Acharya, Engle and Richardson (2012) and Brownlees and Engle (2012), and the *Delta Conditional Value-at-Risk* (ΔCoVaR) of Adrian and Brunnermeier (2011).[26] Very few crisis-related papers made a higher impact both in the academia and on the regulatory debate than this series of papers. Over the past four years, hundreds of research papers have discussed, implemented, and sometimes generalized, these systemic risk measures.[27] Furthermore, in discussions with central bankers and regulators, we learned that these measures are currently used to monitor potentially systemically important firms.

The goal of this paper is to propose a comprehensive comparison of the major systemic risk measures (MES, SES, SRISK, and ΔCoVaR). The systemic risk measures we consider in this paper have nice economic interpretations. First, the MES corresponds to a firm's expected equity loss when market falls below a certain threshold over a given horizon, namely a 2% market drop over one day for the short-run MES, and a 40% market drop over six months for the long-run MES (LRMES). The basic idea is that the banks with the highest MES contribute the most to market declines; thus, these banks are the greatest drivers of systemic risk. Second, the SES and SRISK measure the expected capital shortfall of an institution conditional on a financial crisis occurring. The intuition is that the firm with the largest capital shortfall that occurs precisely during the system crisis, should be considered as the most systemically risky. Third, the CoVaR corresponds to the Value-at-Risk (VaR) of the financial system conditionally on a specific event affecting a given firm. The contribution of a firm to systemic risk (ΔCoVaR) is the difference between its CoVaR when the firm is, or is not, in financial distress. As an illustration, we

that would attract customers, because such banks would be forced to hold more capital and be subject to more intense regulation". Araten and Turner (2013) find that funding cost is significantly lower for SIFIs than for non-SIFIs.

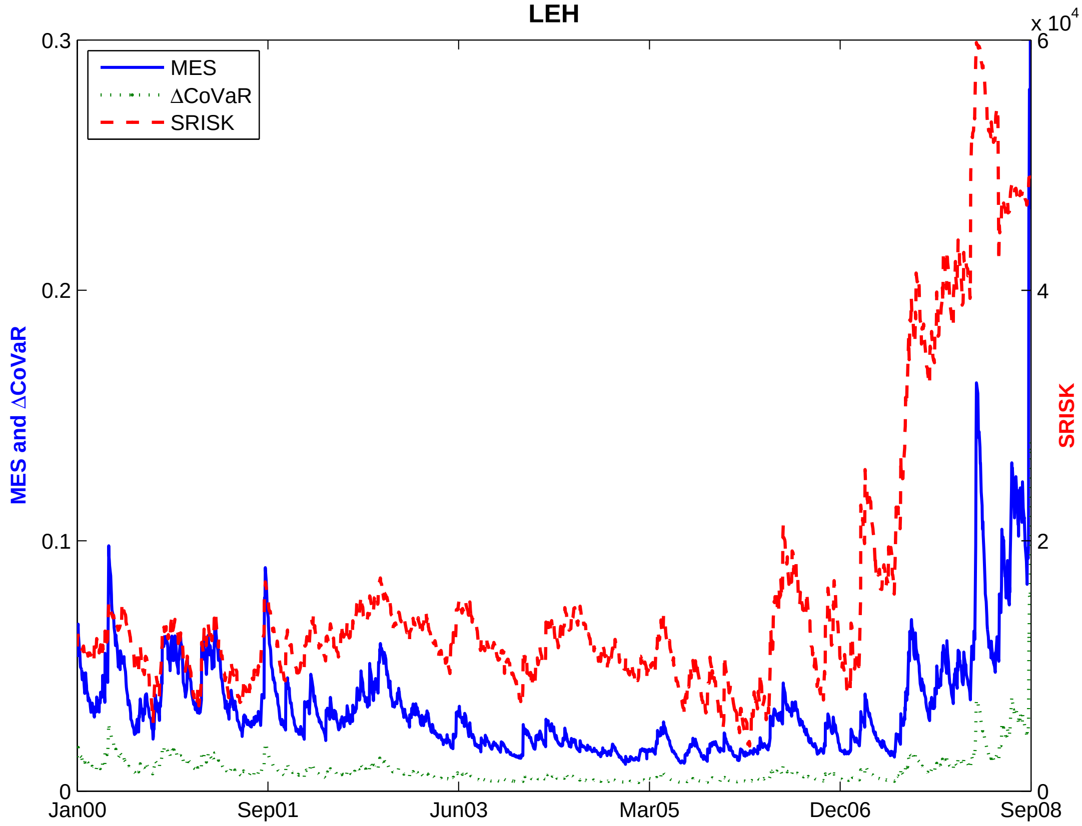
[25]See Elsinger, Lehar and Summer (2006), FSB-IMF-BIS (2009), Basel Committee on Banking Supervision (2011a), Financial Stability Oversight Council (2012a), Gouriéroux, Héam and Monfort (2012), Greenwood, Landier and Thesmar (2012), and Glasserman and Young (2013).

[26]Other related papers include Huang, Zhou and Zhu (2009, 2012), Drehmann and Tarashev (2011b), Gray and Jobst (2011), Kritzman et al. (2011), Acharya and Steffen (2012), Billio et al. (2012), Bisias et al. (2012), Gauthier, Lehar and Souissi (2012), Giglio (2012), Gouriéroux and Monfort (2011), White, Kim and Manganelli (2012), Oh and Patton (2013), and Yang and Zhou (2013).

[27]See for instance Adams, Füss and Gropp (2010), Fong and Wong (2010), Danielson et al. (2011, 2012), Colletaz, Pérignon and Hurlin (2012), Engle, Jondeau and Rockinger (2014), Idier, Lamé and Mésonnier (2012), Lopez-Espinosa et al. (2012a, 2012b), Cao (2013), and Ergun and Girardi (2013). For recent media coverage, see Bloomberg Businessweek (2011), The Economist (2011), and Rob Engle's interview on CNBC (2011). For online computation of systemic risk measures, see the Stern-NYU's V-Lab initiative at http://vlab.stern.nyu.edu/welcome/risk/.

display in Figure 2.1, the evolution of several systemic risk measures for Lehman Brothers between 2000 and 2008. We see that all risk measures raise around 2006 and that SRISK increases much more, in relative terms, than the other measures.

Figure 2.1 Time Series Evolution of Systemic Risk Measures



Notes: The figure displays the MES (solid line, left axis), the ΔCoVaR (dotted line, left axis) and the SRISK (dashed line, right axis) of Lehman Brothers (LEH).

There are two main parts in our analysis. First, we derive the systemic risk measures in a common framework and show theoretically that they can be expressed in terms of market risk measures. In particular, we find that (*i*) MES corresponds to the product of the market's expected shortfall (market tail risk) and the firm beta (firm systematic risk) and that (*ii*) ΔCoVaR corresponds to the product of the firm VaR (firm tail risk) and the linear projection coefficient of the market return on the firm return. Furthermore, (*iii*) we derive conditions under which the different measures lead to similar rankings of SIFIs. Second, we propose an empirical comparison of the systemic risk measures by considering a sample of top US financial institutions over the period 2000 - 2010. This comparison aims to answer the following key questions: Do the different risk measures identify the same SIFIs? And if not, what are the reasons? Our empirical analysis delivers some key insights on systemic risk. First, we show that different risk measures lead to identifying different SIFIs. On most days, there is not a single institution simultaneously identified as a top-10 SIFI by all measures. Second, there is a strong positive relationship between MES and firm beta, which implies that systemic risk rankings of financial institutions based on MES mirror rankings obtained by sorting firms on betas. Third, we reach a similar conclusion for SRISK and liabilities. Fourth, as the empirical ΔCoVaR of a firm is strongly correlated with its VaR, ΔCoVaR brings limited added value over and above VaR to forecast systemic risk. In a linear regression analysis, we show that a one-factor model explains between 83% and 100% of the variability of the systemic risk estimates, which indicates that standard systemic risk measures fall short in capturing the multiple facets of systemic risk.

Our paper makes several contributions to the academic literature on systemic risk. To the best of our knowledge, this is the first attempt to derive the major systemic risk measures within a common framework. Our analytical expressions allow us to uncover the theoretical link between systemic risk and standard financial risks (systematic risk, tail risk, correlation, and beta), as well as firm characteristics such as leverage and market capitalization. Unlike purely empirical horse races, our theoretical comparison is not plagued by estimation risk or concerns about sample composition and sample periods. Another reason for us to not running an empirical horse race is that it is impossible to measure ex post the contribution of a given firm to the risk of the system. As a result, there is no benchmark and we cannot assess the validity of a given measure by analysing its forecasting errors.[28]

The rest of the paper is organized as follows. Section 2.2 provides the general definitions of the three considered systemic risk measures and presents the common framework used for the comparison. Section 2.3 proposes a theoretical analysis of the MES, SRISK, and ΔCoVaR measures. In Section 2.4, we describe the data and present the main empirical findings. Section 2.5 summarizes and concludes.

2.2 Methodology

2.2.1 Definitions

In this section, we provide a formal definition for the considered systemic risk measures. We consider N firms and denote r_{it} the return of firm i at time t. Similarly, the market return is the value-weighted average of all firm returns, $r_{mt} = \sum_{i=1}^{N} w_{it} r_{it}$, where w_{it} denotes the relative market capitalization of firm i.

[28]Sedunov (2012) tests whether measures of systemic risk exposures can forecast financial institutions' returns during systemic crisis periods in 1998 and 2008. Giglio, Kelly and Pruitt (2013) evaluate the empirical success of systemic risk measures, based on their predictive ability for low quantiles of the conditional distribution of macroeconomic outcomes. One could argue that instead one could use as a benchmark the actual list of the Global SIFIs published by the Financial Stability Board (2012), and see which measure can best reproduce it. However, in such an analysis we first must assume the truthfulness of the list and moreover we could always imagine a parametric systemic risk measure sufficiently flexible to reproduce any particular ranking on a given date.

MES and SES

The MES is the marginal contribution of an institution i to systemic risk, as measured by the Expected Shortfall (ES) of the system. Originally proposed by Acharya et al. (2010), the MES was recently extended to a conditional version by Brownlees and Engle (2012). By definition, the ES at the $\alpha\%$ level is the expected return in the worst $\alpha\%$ of the cases, but it can be extended to the general case, in which the returns exceed a given threshold C. Formally, the conditional ES of the system is defined as:[29]

$$ES_{mt}(C) = \mathbb{E}_{t-1}\Big(r_{mt} \mid r_{mt} < C\Big) = \sum_{i=1}^{N} w_{it}\ \mathbb{E}_{t-1}\Big(r_{it} \mid r_{mt} < C\Big). \tag{2.1}$$

Then, the MES corresponds to the partial derivative of the system ES with respect to the weight of firm i in the economy (Scaillet, 2004).[30]

$$MES_{it}(C) = \frac{\partial ES_{mt}(C)}{\partial w_{it}} = \mathbb{E}_{t-1}\Big(r_{it} \mid r_{mt} < C\Big). \tag{2.2}$$

The MES can be viewed as a natural extension of the concept of marginal VaR proposed by Jorion (2007) to the ES, which is a coherent risk measure (see Artzner et al., 1999). It measures the increase in the risk of the system (measured by the ES) induced by a marginal increase in the weight of firm i in the system. The higher the firm MES, the higher is the individual contribution of the firm to the risk of the financial system.

An extension of the MES is the Systemic Expected Shortfall (SES). The latter corresponds to the amount a bank's equity drops below its target level (defined as a fraction k of assets) in case of a systemic crisis when aggregate capital is less than k times aggregate assets:

$$\frac{SES_{it}}{W_{it}} = k\ L_{it} - 1 - \mathbb{E}_{t-1}\Big(r_{it} \mid \sum_{i=1}^{N} W_{it} < k \sum_{i=1}^{N} A_{it}\Big) \tag{2.3}$$

where L_{it} is the leverage (A_{it}/W_{it}), A_{it} denotes the total assets, and W_{it} is the market capitalization or market value of equity. Acharya et al. (2010) show that the conditional expectation term can be expressed as a linear function of the MES:

$$SES_{it} = \Big(k\ L_{it} - 1 + \theta\ MES_{it} + \Delta_i\Big)\ W_{it} \tag{2.4}$$

where θ and Δ_i are constant terms.

SRISK

The SRISK measure proposed by Acharya, Engle and Richardson (2012) and Brownlees and Engle (2012) extends the MES in order to take into account both the liabilities

[29]We follow the original notations of the different authors: ES, MES, VaR, CoVaR and ΔCoVaR are typically negative whereas SES and SRISK are typically positive.

[30]To simplify the notation, we use MES_{it} (respectively ES_{it}) instead of $MES_{i,t|t-1}$ (respectively $ES_{i,t|t-1}$), but it should be understood as the conditional MES (respectively ES) computed at time t given the information available at time $t-1$.

and the size of the financial institution. The SRISK corresponds to the expected capital shortfall of a given financial institution, conditional on a crisis affecting the whole financial system. In this perspective, the firms with the largest capital shortfall are assumed to be the greatest contributors to the crisis and are the institutions considered as most systemically risky. We follow Acharya, Engle and Richardson (2012) and define the SRISK as:

$$SRISK_{it} = \max \left[0 \ ; \ \overbrace{k \ (D_{it} + (1 - LRMES_{it})W_{it})}^{\textit{Required Capital}} - \overbrace{(1 - LRMES_{it})W_{it}}^{\textit{Available Capital}} \right] \tag{2.5}$$

where k is the prudential capital ratio and D_{it} is the book value of total liabilities. Note that if we define the leverage as $L_{it} = (D_{it} + W_{it})/W_{it}$, SRISK becomes:

$$SRISK_{it} = \max \Big[0 \ ; \ [k \ (L_{it} - 1) - (1 - k) \ (1 - LRMES_{it})] \, W_{it} \Big] \tag{2.6}$$

and we notice that SRISK increases with the leverage. We clearly see that the expressions for SRISK and SES in equations (2.4) and (2.6) are almost identical. As a result, in the rest of the paper we only focus on SRISK.

The SRISK also considers the interconnection of a firm with the rest of the system through the long-run marginal expected shortfall (LRMES). The latter corresponds to the expected drop in equity value the firm would experiment if the market were to fall by more than a given threshold within the next six months. Acharya, Engle and Richardson (2012) propose to approximate it using the daily MES (defined for a threshold C equal to -2%) as $LRMES_{it} \simeq 1 - \exp(18 \times MES_{it})$. This approximation represents the firm expected loss over a six-month horizon, obtained conditionally on the market falling by more than 40% within the next six months (for more details, see Acharya, Engle and Richardson, 2012).

ΔCoVaR

The last systemic risk measure is the ΔCoVaR of Adrian and Brunnermeier (2011). This measure is based on the concept of Value-at-Risk, denoted VaR(α), which is the maximum loss within the α%-confidence interval (see Jorion, 2007). Then, the CoVaR corresponds to the VaR of the market return obtained conditionally on some event $\mathbb{C}(r_{it})$ observed for firm i:[31]

$$\Pr \left(r_{mt} \leq CoVaR_t^{m|\mathbb{C}(r_{it})} \;\middle|\; \mathbb{C}(r_{it}) \right) = \alpha. \tag{2.7}$$

The ΔCoVaR of firm i is then defined as the difference between the VaR of the financial system conditional on this particular firm being in financial distress and the VaR of the financial system conditional on firm i being in its median state. To define the distress of

[31] To simplify the notations, we neglect the conditioning with respect to past information, but the CoVaR is a conditional VaR with respect to both $\mathbb{C}(r_{it})$ observed for firm i and the past returns $r_{m,t-k}$.

a financial institution, various definitions of $\mathbb{C}(r_{it})$ can be considered. Because they use a quantile regression approach, Adrian and Brunnermeier (2011) consider a situation in which the loss is precisely equal to its VaR:

$$\Delta CoVaR_{it}(\alpha) = CoVaR_t^{m|r_{it}=VaR_{it}(\alpha)} - CoVaR_t^{m|r_{it}=Median(r_{it})}. \tag{2.8}$$

A more general approach would consist in defining the financial distress of firm i as a situation in which the losses exceed its VaR (see Ergun and Girardi, 2012):

$$\Delta CoVaR_{it}(\alpha) = CoVaR_t^{m|r_{it}\leq VaR_{it}(\alpha)} - CoVaR_t^{m|r_{it}=Median(r_{it})}. \tag{2.9}$$

2.2.2 A Common Framework

The different systemic risk measures analyzed in this paper have been developed within very different frameworks. For instance, Adrian and Brunnermeier (2011) allow for tail dependence and use a quantile regression approach to estimate the ΔCoVaR. Differently, Brownlees and Engle (2012) model time-varying linear dependencies and use a multivariate GARCH-DCC model to compute the MES. Hence, their direct comparison is not straightforward since some empirical differences may be due to the estimation strategies. Differently, we derive all these risk measures within a unified theoretical framework to provide a level playing field. Following Brownlees and Engle (2012), we consider a bivariate GARCH process for the demeaned returns:

$$r_t = H_t^{1/2}\ \nu_t \tag{2.10}$$

where $r_t' = (r_{mt}\ r_{it})$ denotes the vector of market and firm returns and where the random vector $\nu_t' = (\varepsilon_{mt}\ \xi_{it})$ is *i.i.d.* and has the following first moments: $\mathbb{E}(\nu_t) = 0$ and $\mathbb{E}(\nu_t\nu_t') = I_2$, a two-by-two identity matrix. The H_t matrix denotes the conditional variance-covariance matrix:

$$H_t = \begin{pmatrix} \sigma_{mt}^2 & \sigma_{it}\ \sigma_{mt}\ \rho_{it} \\ \sigma_{it}\ \sigma_{mt}\ \rho_{it} & \sigma_{it}^2 \end{pmatrix} \tag{2.11}$$

where σ_{it} and σ_{mt} denote the conditional standard deviations and ρ_{it} the conditional correlation. No particular assumptions are made about the bivariate distribution of the standardized innovations ν_t, which is assumed to be unknown. We only assume that the time-varying conditional correlations ρ_{it} fully captures the dependence between the firm and market returns.[32] Formally, this assumption implies that the standardized innovations ε_{mt} and ξ_{it} are independently distributed at time t.

2.3 A Theoretical Comparison of Systemic Risk Measures

2.3.1 MES

Given Equations (2.10) and (2.11), the MES can be expressed as a function of the firm return volatility, its correlation with the market return, and the comovement of the tail

[32] We will relax this assumption in the empirical analysis in Section 2.4.

of the distribution (see Appendix 2.6.1):

$$\begin{aligned} MES_{it}(C) &= \sigma_{it}\ \rho_{it}\ \mathbb{E}_{t-1}\left(\varepsilon_{mt} \mid \varepsilon_{mt} < \frac{C}{\sigma_{mt}}\right) \\ &\quad + \sigma_{it}\ \sqrt{1-\rho_{it}^2}\ \mathbb{E}_{t-1}\left(\xi_{it} \mid \varepsilon_{mt} < \frac{C}{\sigma_{mt}}\right). \end{aligned} \tag{2.12}$$

The MES is expressed as a weighted function of the tail expectation of the standardized market residual and the tail expectation of the standardized idiosyncratic firm residual. As the dependence between market and firm returns is completely captured by their correlation, the conditional expectation $\mathbb{E}_{t-1}\left(\xi_{it} \mid \varepsilon_{mt} < \frac{C}{\sigma_{mt}}\right)$ is null. In order to facilitate the comparison with the ΔCoVaR, we consider a threshold C equal to the conditional VaR of the market return, which is defined as $\Pr\left[r_{mt} < VaR_{mt}(\alpha) | \mathcal{F}_t\right] = \alpha$ where $\mathcal{F}_t$ denotes the information set available at time t.

Proposition 1. *The MES of a given financial institution i is proportional to its systematic risk, as measured by its time-varying beta. The proportionality coefficient is the expected shortfall of the market:*

$$MES_{it}(\alpha) = \beta_{it}\ ES_{mt}(\alpha) \tag{2.13}$$

where $\beta_{it} = cov(r_{it}, r_{mt})/var(r_{mt}) = \rho_{it}\sigma_{it}/\sigma_{mt}$ denotes the time-varying beta of firm i and $ES_{mt}(\alpha) = \mathbb{E}_{t-1}(r_{mt} \mid r_{mt} < VaR_{mt}(\alpha))$ *is the expected shortfall of the market.*

The proof of Proposition 1 is in Appendix 2.6.1.[33] This proposition has two main implications. First, on a given date, the systemic risk ranking of financial institutions based on MES (in absolute value) is strictly equivalent to the ranking that would be produced by sorting firms according to their betas. Indeed, since the system ES is not firm-specific, the greater the sensitivity of the return of a firm with respect to the market return, the more systemically-risky the firm is. Consequently, under our assumptions, identifying SIFIs using MES is equivalent to consider the financial institutions with the highest betas. Second, for a given financial institution, the time profile of its systemic risk measured by its MES may be different from the evolution of its systematic risk measured by its conditional beta. Since the market ES may not be constant over time, forecasting the systematic risk of firm i may not be sufficient to forecast the future evolution of its contribution to systemic risk.

Note that Proposition 1 is robust with respect to the choice of the threshold C that determines the system crisis. For any threshold $C \in \mathbb{R}$, the MES is still proportional to the time-varying beta (see proof in Appendix 2.6.1). The only difference is that the proportionality coefficient, $\mathbb{E}_{t-1}(r_{mt} \mid r_{mt} < C)$, is different from the system ES if $C \neq VaR_{mt}(\alpha)$. However, this coefficient remains common to all firms.

[33] For some particular distributions, both the ES and the MES of the market returns can be expressed in closed form. For instance, if ε_{mt} follows a standard normal distribution, then $VaR_{mt}(\alpha) = \sigma_{mt}\Phi^{-1}(\alpha)$ and $ES_{mt}(\alpha) = -\sigma_{mt}\phi(\Phi^{-1}(\alpha))\alpha$, where $\phi(.)$ and $\Phi(.)$, respectively, denote the standard normal probability distribution function and cumulative distribution function. Therefore, $MES_{it}(\alpha) = -\beta_{it}\sigma_{mt}\lambda(\Phi^{-1}(\alpha))$, where $\lambda(z) = \phi(z)\Phi(z)$ denotes the Mills ratio.

2.3.2 SRISK

We show in Section 2.2 that SRISK is a function of the MES. As a result, a corollary of Proposition 1 is that SRISK can be expressed as a function of the beta, leverage, and market capitalization of the financial institution:

$$SRISK_{it} \simeq \max \left[0 \ ; \ \left[k \ (L_{it} - 1) - (1-k) \exp \left(18 \times \beta_{it} \times ES_{mt}(\alpha) \right) \right] W_{it} \right]. \tag{2.14}$$

SRISK is an increasing function of the systematic risk, as measured by the conditional beta since $ES_{mt}(\alpha)$ is typically a negative number and the prudential capital ratio k is smaller than one. However, unlike with MES, systemic-risk rankings based on SRISK are not equivalent to rankings based on betas. SRISK-based rankings also depend on the leverage and on the market capitalization of the financial institution.

Accounting for market capitalization and liabilities in the definition of the systemic risk measure tends to increase the systemic risk score of large firms. This result is in line with the too-big-to-fail paradigm, whereas the MES tends to be naturally attracted by interconnected institutions (through the beta), which is more in line with the too-interconnected-to-fail paradigm (Markose et al., 2010). In that sense, the SRISK can be viewed as a compromise between both paradigms.

2.3.3 ΔCoVaR

In our theoretical framework, it is also possible to express ΔCoVaR, defined for a conditioning event $\mathbb{C}(r_{it}) : r_{it} = VaR_{it}(\alpha)$, as a function of the conditional correlations, volatilities, and VaR. Given Equations (2.10) and (2.11), we obtain the following result:

Proposition 2. *The $\Delta CoVaR$ of a given financial institution i is proportional to its tail risk, as measured by its VaR. The proportionality coefficient corresponds to the linear projection coefficient of the market return on the firm return.*

$$\Delta CoVaR_{it}(\alpha) = \gamma_{it} \ \left[VaR_{it}(\alpha) - VaR_{it}(0.5) \right] \tag{2.15}$$

where $\gamma_{it} = \rho_{it}\sigma_{mt}/\sigma_{it}$. If the marginal distribution of the returns is symmetric around zero, $\Delta CoVaR$ is strictly proportional to VaR:

$$\Delta CoVaR_{it}(\alpha) = \gamma_{it} \ VaR_{it}(\alpha). \tag{2.16}$$

The proof of Proposition 2 is in Appendix 2.6.2.[34] The fact that the proportionality coefficient between ΔCoVaR and VaR is firm-specific has some strong implications. Let us, for instance, consider two financial institutions i and j, with $VaR_{it} < VaR_{jt}$. Given the relative correlations between the returns of firms i and j with the market return (respectively ρ_{it} and ρ_{jt}), and the volatilities σ_{it} and σ_{jt}, we could observe $\Delta CoVaR_{it} <$

[34] Adrian and Brunnermeier (2011) derive the CoVaR and the ΔCoVaR under the normality assumption. They show that $\Delta CoVaR_{it}(\alpha) = \rho_{it}\sigma_{mt}\Phi^{-1}(\alpha)$ or equivalently $\gamma_{it}\sigma_{it}\Phi^{-1}(\alpha)$, where $\sigma_{it}\Phi^{-1}(\alpha)$ denotes the VaR(α) of the firm.

$\Delta CoVaR_{jt}$ or $\Delta CoVaR_{it} > \Delta CoVaR_{jt}$. This means that the most risky institution in terms of VaR is not necessarily the most systemically risky institution. In other words, on a given date, the systemic risk ranking over N financial institutions based on ΔCoVaR is not equivalent to a VaR-based ranking. In that sense, ΔCoVaR is not equivalent to VaR as already pointed out by Adrian and Brunnermeier (2011) in their Figure 1. Indeed, they report a weak relationship between an institution's risk in isolation, measured by its VaR, and its contribution to system risk, measured by its ΔCoVaR. However, for a given institution, ΔCoVaR is proportional to VaR. Consequently, forecasting the future evolution of the contribution of firm i to systemic risk is equivalent to forecast its risk in isolation.

There are three comments to be made here. First, the proportionality coefficient in Equation (2.16), γ_{it}, is not a beta as it is the linear projection coefficient of the market return on the firm return, and not the opposite. Second, the proportionality coefficient is not always time-varying. For instance, when the variance-covariance matrix is constant or when ΔCoVaR is estimated through quantile regression as in Adrian and Brunnermeier (2011), the coefficient is constant. Third, Proposition 2 remains valid when ΔCoVaR is estimated using market-valued total asset returns instead of stock returns.[35] The proportionality coefficient in equation (2.16) would then depend on the firm leverage and the average leverage in the market.

2.3.4 Comparing Systemic-Risk Rankings

The main objective of any systemic risk analysis is to rank firms according to their systemic risk contribution and, in turn, identify the SIFIs. The key question is then to determine whether the different systemic risk measures lead to the same conclusion. A natural way to answer this question is to analyze their ratio.

Proposition 3. *For a given financial institution i at time t, the ratio between its ΔCoVaR and its MES is:*

$$\frac{\Delta CoVaR_{it}(\alpha)}{MES_{it}(\alpha)} = f_{it} \times g_{mt}. \tag{2.17}$$

If the marginal distribution of the firm return is symmetric, $f_{it} = VaR_{it}(\alpha)/\sigma_{it}^2$ *and* $g_{mt} = \sigma_{mt}^2/ES_{mt}(\alpha)$. *If the distribution is not symmetric,* $VaR_{it}(\alpha)$ *is replaced by* $VaR_{it}(\alpha) - VaR_{it}(0.5)$.

The ΔCoVaR/MES ratio is the product of two terms. The first term is firm-specific (f_{it}), whereas the second is common to all firms (g_{mt}).[36] The fact that this ratio is firm-

[35] Adrian and Brunnermeier (2011) define the growth rate of market-valued total assets as $\widetilde{r}_{it} = (W_{it}\ L_{it} - W_{i,t-1}\ L_{i,t-1})/(W_{i,t-1}\ L_{i,t-1})$. If we define $r_{it} = (W_{it} - W_{i,t-1})/W_{i,t-1}$ and $l_{it} = (L_{it} - L_{i,t-1})/L_{i,t-1}$, we get $1 + \widetilde{r}_{it} = (1 + r_{it})(1 + l_{it})$. Quarterly leverage data need to be linearly interpolated to generate daily leverage data.

[36] If we assume normality for the marginal distributions of ε_{mt} and ξ_{it}, this ratio has a closed form:

$$\frac{\Delta CoVaR_{it}(\alpha)}{MES_{it}(\alpha)} = -\left(\frac{\sigma_{mt}}{\sigma_{it}}\right)\frac{\Phi^{-1}(\alpha)}{\lambda(\Phi^{-1}(\alpha))}.$$

specific implies that the systemic risk rankings based on the two measures may not be the same. Consider two different financial institutions i and j such that i is more systemically risky than j according to ΔCoVaR, $\Delta CoVaR_{it} < \Delta CoVaR_{jt}$. It is possible to observe a situation where i is less risky than j according to the MES measure, $MES_{it} > MES_{jt}$. In other words, the SIFIs identified by the MES and by the ΔCoVaR may not be the same. Note that this result can be extended to the SRISK since the latter depends on MES.

Our theoretical framework also permits to derive conditions under which both rankings are convergent, respectively divergent.

Proposition 4. *A financial institution i is more systemically risky that an institution j according to the MES and the ΔCoVaR measures, $MES_{it}(\alpha) \leq MES_{jt}(\alpha)$ and $\Delta CoVaR_{it}(\alpha) \leq \Delta CoVaR_{jt}(\alpha)$, if:*

$$\rho_{it} \geq \max\left(\rho_{jt}, \frac{\rho_{jt}\ \sigma_{jt}}{\sigma_{it}}\right) \tag{2.18}$$

and if the conditional distributions of the two standardized returns r_{it}/σ_{it} and r_{jt}/σ_{jt} are identical and location-scale.

The proof of Proposition 4 is in Appendix 2.6.3.[37] The interpretation of this result works as follows. If $\sigma_{it} \geqslant \sigma_{jt}$, inequality (2.18) becomes $\rho_{it} \geq \rho_{jt}$. In the other case, if $\sigma_{it} < \sigma_{jt}$, the inequality becomes $\rho_{it} \geq \rho_{jt}\sigma_{jt}/\sigma_{it}$. In both cases, the interpretation is the same: the higher the correlation between the returns of the SIFIs and the market, the more likely it is that MES and $\Delta CoVaR$ will lead to a convergent diagnostic. This result comes from the fact that correlation captures both the sensitivity of the system return with respect to the firm return (ΔCoVaR dimension) and the sensitivity of the firm return with respect to the system return (MES dimension).

The systemic risk rankings based on SRISK and ΔCoVaR can also be compared. In this case, the comparison depends on the liabilities and market capitalizations of the two firms. For simplicity, let us consider two financial institutions with the same level of liabilities.

Proposition 5. *A financial institution i is more systemically risky than a financial institution j (with the same level of liabilities) according to the SRISK and the ΔCoVaR measures, $SRISK_{it}(\alpha) \geq SRISK_{jt}(\alpha)$ and $\Delta CoVaR_{it}(\alpha) \leq \Delta CoVaR_{jt}(\alpha)$, if*

$$\rho_{it} \geq \rho_{jt} \quad \textit{and} \quad W_{it} \leq W_{jt} \times \exp\left[18 \times ES_{mt}(\alpha) \times (\beta_{jt} - \beta_{it})\right] \tag{2.19}$$

where W_{it} and W_{jt} denote the market capitalizations of both firms.

The proof of Proposition 5 is in Appendix 2.6.4. ΔCoVaR and SRISK provide a similar systemic risk ranking if and only if (i) the correlation of the riskier firm with the

[37] If the conditional distributions are not identical and/or not location-scale, the corresponding condition has the same form and implies that the correlation ρ_{it} exceeds a given threshold (see Appendix 2.6.3).

system is higher than the correlation of the less risky institution and (*ii*) if the riskier firm has the lower market capitalization. Since both firms are assumed to have the same level of liabilities, this condition means that the ranking are similar if the riskier financial institution has the higher leverage. In other words, if the SIFIs have a high leverage and are very correlated with the system, ΔCoVaR and SRISK will lead to the same conclusion. As soon as one of these conditions is violated, the ranking of the financial institutions will be divergent.

2.4 An Empirical Comparison of Systemic Risk Measures

We have shown in our theoretical analysis that systemic risk measures (*i*) can be expressed as linear transformations of market risk measures (ES, VaR, beta) and (*ii*) lead similar rankings under rather restrictive conditions. These results have been derived within the common framework presented in Section 2.2.2. However, in practice, the dependence between financial asset returns may be richer (i.e. not linear) than in Section 2.2.2 and thus our results may not hold in real financial markets.

For this reason, in this section, we relax the assumptions made in Equations (2.10) and (2.11) for asset returns. In our empirical analysis, we implement the same estimation methods as in the original papers presenting the MES, SRISK, and CoVaR, and we use the same sample as in Acharya et al. (2010) and Brownlees and Engle (2012). This sample contains all U.S. financial firms with a market capitalization greater than \$5 billion as of end of June 2007 (see Appendix 2.6.5 for a list of the 94 sample firms). For our sample period, January 3, 2000 - December 31, 2010, we extract daily firm stock returns, value-weighted market index returns, number of shares outstanding, and daily closing prices from CRSP. Quarterly book values of total liabilities are from COMPUSTAT. Following Brownlees and Engle (2012), we estimate the MES and SRISK using a GARCH-DCC model. The coverage rate is fixed at 5%, and the threshold C is fixed to the unconditional market daily VaR at 5%, which is equal to 2% in our sample. The ΔCoVaR is estimated with a quantile regression as proposed by Adrian and Brunnermeier (2011). We discuss in detail the estimation techniques of all systemic risk measures in Appendix 2.6.6.

2.4.1 Rankings: SIFI or not SIFI?

In practice, systemic risk measures are used to classify firms between SIFIs and non-SIFIs (Financial Stability Board, 2012). The formers are more closely scrutinized by regulators and are subject to additional capital requirements and/or liquidity buffers. Within a given bucket of SIFIs, the level of extra capital requirement is the same regardless of the exact ranking of the firm within the bucket. The goal is then to identify the top tier banks in terms of contribution to the risk of the system. Of lesser importance is the exact value of the systemic risk measures or the exact ranking of the bank. In order to compare the SIFIs identified by several systemic risk measures, we need to set the size of the SIFI group. In the rest of the analysis, we use the top 10 financial institutions, which corresponds to approximately 10% of our sample. It is also close to the actual number of US SIFIs (namely 8) identified by the Financial Stability Board (2012) in its list of global systemically important banks. As a robustness check, we also provide results based on the top 20 financial institutions.

The main finding from this preliminary analysis is that the *different* risk measures identify *different* SIFIs. For instance, Table 2.1 displays the tickers of the top 10 financial institutions according to their systemic risk contribution measured by the MES, SRISK, and ΔCoVaR, respectively, for the last day of our sample period (December 31, 2010). On that day, there is not a single institution simultaneously identified as a SIFI by the three measures. Only two financial institutions (Bank of America and American International Group) are simultaneously identified by MES and SRISK, whereas ΔCoVaR identifies only three financial institutions (H&R Block, Marshall & Ilsley, and Janus Capital) in common with MES but none with SRISK. Furthermore, the SRISK-based top 10 list is clearly tilted towards the largest financial institutions (Bank of America, Citigroup, JP Morgan, etc.), whereas it is not necessarily the case for MES and ΔCoVaR. Indeed, these measures do not take into account the market capitalization and level of liabilities of the financial institutions. Note that we reach a similar conclusion when we consider the top 20 financial institutions, with only three firms being simultaneously identified by the three risk measures (see Appendix 2.6.7).

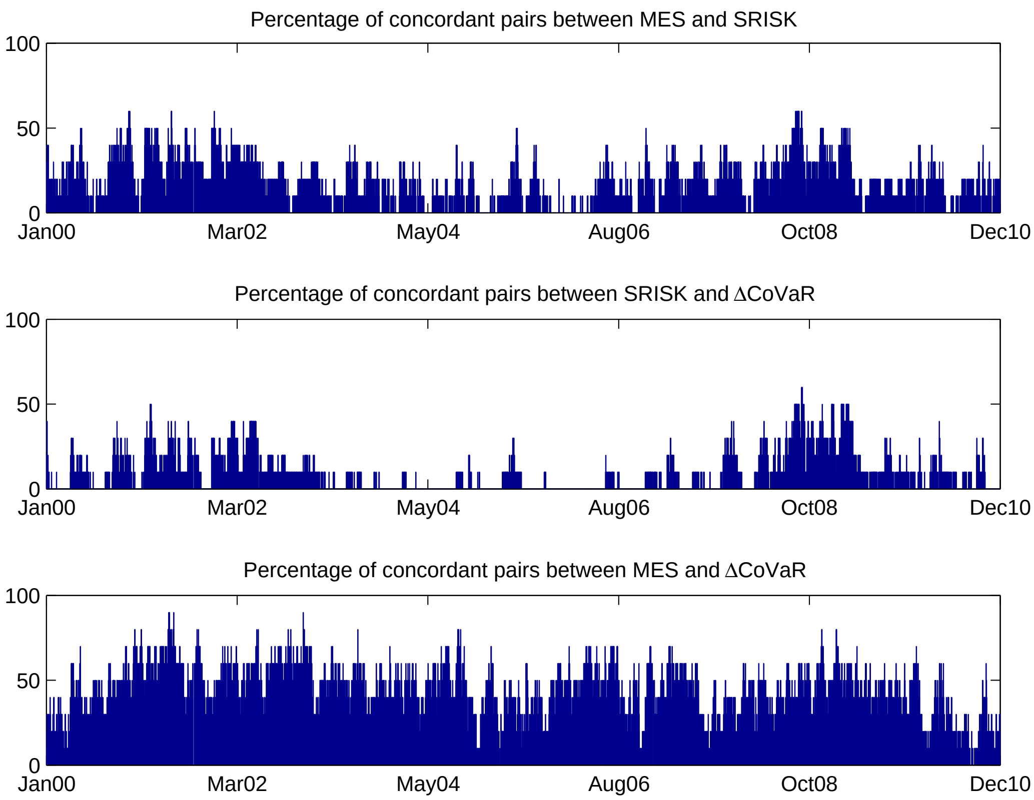
Table 2.1 Systemic Risk Rankings

Rank	MES	SRISK	ΔCoVaR
1	MBI	BAC	HRB
2	AIG	C	MI
3	MI	JPM	BEN
4	CBG	MS	CIT
5	RF	AIG	WU
6	LM	MET	AIZ
7	JNS	PRU	AXP
8	HRB	HIG	JNS
9	BAC	SLM	NYB
10	UNM	LNC	MTB

Notes: The column labeled MES displays the ranking of the top 10 financial institutions based on MES, ranked from most to least risky. The following two columns display the top 10 financial institutions based on SRISK and ΔCoVaR, respectively. The ranking is for December 31, 2010. See Appendix 2.6.5 for the list of firm names and tickers.

The findings about diverging rankings is not specific to any particular date. Indeed, out of 2,767 days in our sample, there are 1,263 days (45.7%) during which none of the 94 financial institutions is jointly included in the top 10 ranking of the three risk measures. Figure 2.2 shows the daily percentage of concordant pairs between the top 10 SIFIs identified by the different risk measures. On average, the percentage of concordant pairs between MES and SRISK is 18.9%, which means that, on average, only two SIFIs out of ten are common to both measures. Over our 11-year sample, this percentage has ranged between 0% and 60%; the latter percentage corresponding to the peak of the crisis in October 2008. During a crisis, the MES tends to rise because asset correlation goes to one and both beta and ES increase. Similarly, the SRISK is rising because both leverage and correlation increase and market capitalization drops (see Equation 2.14). The figures are much lower for SRISK and ΔCoVaR, with on average 9.9% of concordant pairs. The highest level of similarity is obtained for MES and ΔCoVaR, with an average percentage of concordant pairs of 43%. We see in Appendix 2.6.7 that the conclusion remains the same when we focus on the top 20 firms.

Figure 2.2 Different Risk Measures, Different SIFIs



Notes: These figures show the daily percentage of concordant pairs between the top ten financial institutions based one MES and SRISK (top panel), the top 10 financial institutions based on SRISK and ΔCoVaR (middle panel), and the top 10 financial institutions based on ΔCoVaR and MES (bottom panel).

Even if these systemic risk measures are divergent, they deliver a consistent ranking for a given institution. Indeed, for each measure, we compute the Kendall rank-order correlation coefficient between the systemic risk ranking obtained at time t and the one obtained at time $t-1$. The average correlations are 91.3% for MES, 97.7% for SRISK, and 93.4% for ΔCoVaR, and are always statistically significant. This result indicates that the rankings produced by these measures are stable through time. This is a nice property to have since it would make little sense for a measure to regularly classify a bank as SIFI on one day, and as non-SIFI on the following day. Therefore, the divergence of the systemic risk rankings is not due to the instability of a particular measure but instead to their fundamental differences.

2.4.2 Main Forces Driving Systemic Risk Rankings

After having shown that rankings vary across systemic risk measures, we investigate the reasons for these variations. We display in Table 2.2 the top 10 SIFIs, as of December 31, 2010, according to the three systemic risk measures, as well as the top 10 firms based on market capitalization, liabilities, leverage, beta, and VaR.[38] There are three striking results in this table. First, MES and beta tend to identify the same SIFIs. On that day, seven out of the ten highest beta firms are also identified among the top 10 SIFIs according to their MES. Even if the rankings provided by the two measures are not exactly the same, the 70% match between the MES and beta provide empirical support to Proposition 1. Indeed, the ranking based on MES is, in practice, mainly driven by systematic risk. Second, the SRISK-based ranking is mainly sensitive to the liabilities/leverage of the firms. We have shown in the previous section, that the SRISK can be considered as a compromise between the too-big-to-fail paradigm (through the liabilities) and the too-interconnected-to-fail paradigm (through the beta). However, in practice the SRISK-based ranking seems to be largely determined by the indebtedness of the firms. On that day, eight out of the top 10 SIFIs identified by the SRISK, are also the financial institutions with the highest level of liabilities and seven have the highest leverage. On the contrary, only two are in the high-beta list. Third, the ΔCoVaR ranking is not determined by the VaR, since only three out of the top 10 SIFIs are also in the high-VaR list. These results are by no means specific to this date as shown in Figure 2.3 and remain pervasive during the entire sample period. Furthermore, they also hold valid when we consider the top 20 firms.

We investigate further the relationship between MES and beta in Figure 2.4. This scatter plot compares the average MES, $\overline{MES}_i(\alpha) = T^{-1}\sum_{t=1}^{T}|MES_{it}(\alpha)|$, to the average beta, $\overline{\beta}_i = T^{-1}\sum_{t=1}^{T}\beta_{it}$, for the 61 firms that have been continuously traded during our sample period.[39] This plot confirms the strong relationship between MES (y-axis)

[38] See Appendix 2.6.6 for a discussion of the estimation of the firms' beta and VaR.

[39] The data requirement allows us to estimate the average ES of the market return over the same period for all firms.

and firm beta (x-axis). In line with Proposition 1, the OLS estimated slope coefficient (0.0248) is extremely close to the unconditional ES of the market at 5%, 0.0252 or 2.52% (see Equation 2.13).[40] The main implication of this result is that systemic risk rankings of financial institutions based on their MES tend to mirror rankings obtained by sorting firms on betas.

Table 2.2 Systemic Risk Rankings and Firm Characteristics

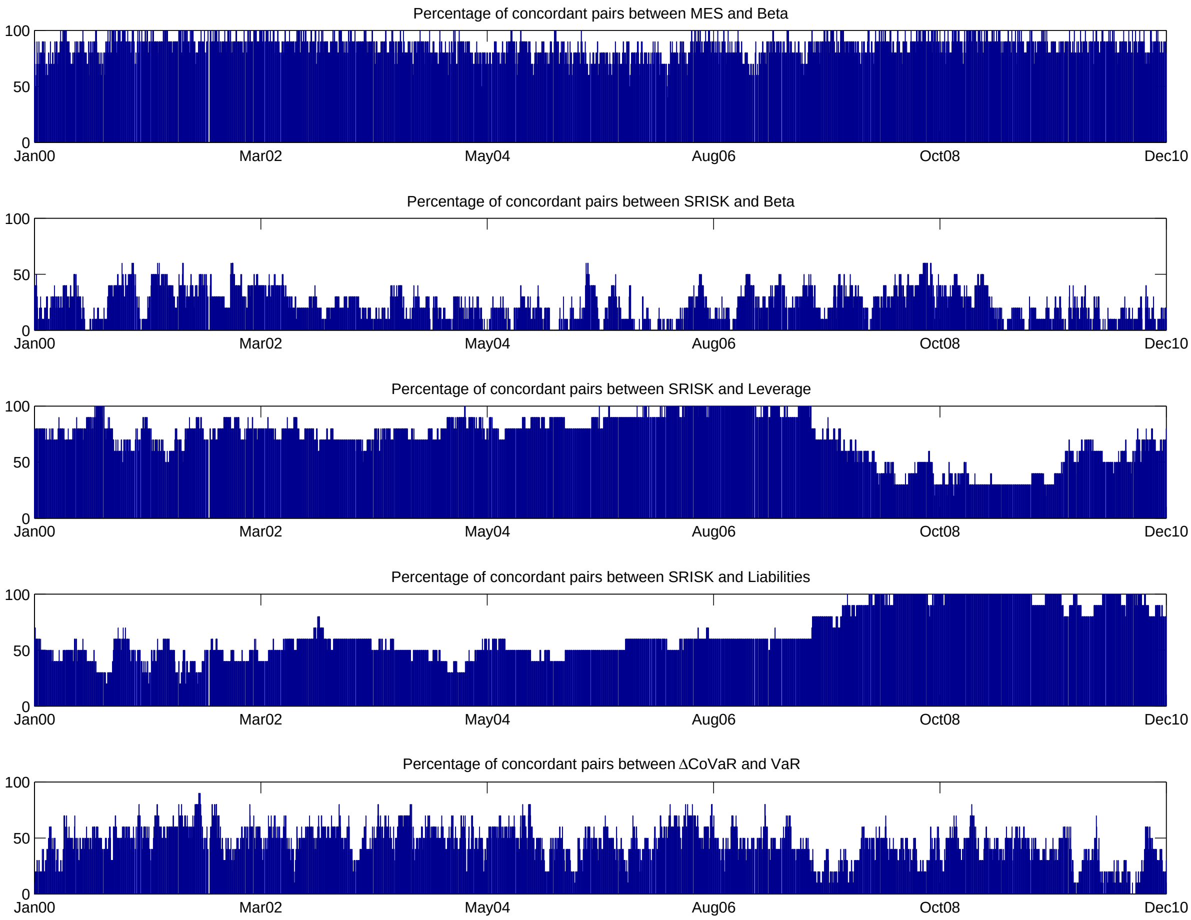
Rank	MES	SRISK	ΔCoVaR	MV	LTQ	LVG	β	VaR
1	MBI	BAC	HRB	JPM	BAC	SLM	MBI	MBI
2	AIG	C	MI	WFC	JPM	HIG	LM	MI
3	MI	JPM	BEN	C	C	LNC	JNS	AIG
4	CBG	MS	CIT	BAC	WFC	MS	MI	RF
5	RF	AIG	WU	GS	GS	PRU	CBG	HRB
6	LM	MET	AIZ	BRK	MS	MET	AIG	SNV
7	JNS	PRU	AXP	USB	MET	GNW	ACAS	HBAN
8	HRB	HIG	JNS	AXP	AIG	BAC	AMTD	BAC
9	BAC	SLM	NYB	MET	PRU	AIG	BAC	FITB
10	UNM	LNC	MTB	MS	HIG	RF	ETFC	JNS

Pairs	MES	SRISK	ΔCoVaR	MV	LTQ	LVG	β	VaR
SRISK	2	–						
ΔCoVaR	3	0	–					
MV	1	5	1	–				
LTQ	2	8	0	7	–			
LVG	3	8	0	3	6	–		
β	7	2	2	1	2	2	–	
VaR	7	2	3	1	2	3	5	–

Notes: In the upper panel, the column labeled MES displays the ranking of the top 10 financial institutions based on MES, listed from most to least risky. The following seven columns display the top 10 financial institutions based on SRISK, ΔCoVaR, market value of equity (MV), liabilities (LTQ), leverage (LVG), conditional beta (β), and VaR, respectively. In the lower panel, we report the number of concordant pairs between two risk measures or firm characteristics. The ranking is for December 31, 2010. See Appendix 2.6.5 for the list of firm names and tickers.

[40]Similar results (not reported) are obtained when we consider unconditional (constant) betas rather than conditional betas, or when we consider the firm MES and beta at a given point in time rather than averages.

Figure 2.3 Driving Forces of Systemic Risk Rankings

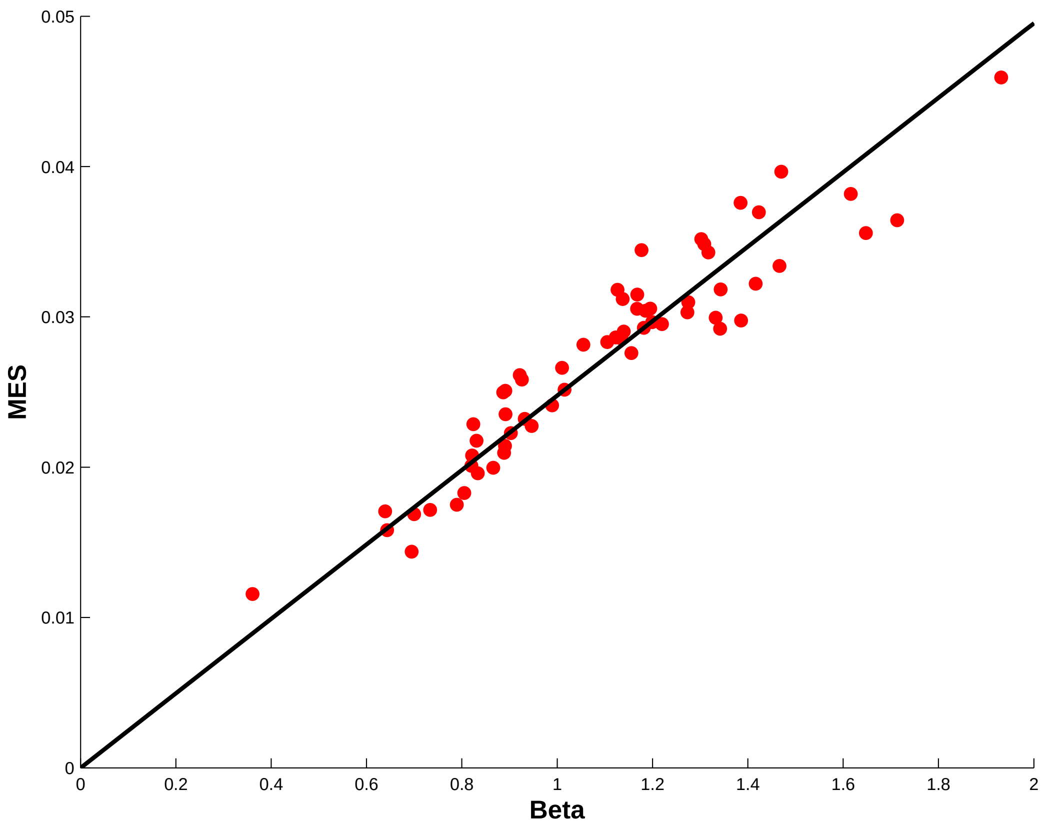


Notes: The top figure shows the daily percentage of concordance between the top 10 financial institutions given the MES and the top 10 financial institutions given the beta. The next three figures show the daily percentage of concordance between the first 10 financial institutions given the SRISK and the first 10 financial institutions given the beta, leverage or liabilities. The bottom figure shows the daily percentage of concordance between the top 10 financial institutions given the ΔCoVaR and the top 10 financial institutions given the VaR.

Should we worry about the fact that MES and beta give similar rankings? We think that this is a serious concern for the following reasons. First, if beta is believed to be a good proxy for systemic risk, why not ranking firms on betas in the first place? Second, this leads to confusion between *systemic risk* and *systematic risk* (market risk). The latter being already accounted for in the banking regulation since the 1996 Amendment of the Basel Accord as regulatory capital depends on the banks' market risk VaR. Third, betas tend to increase during economic downturns, which makes MES procyclical.

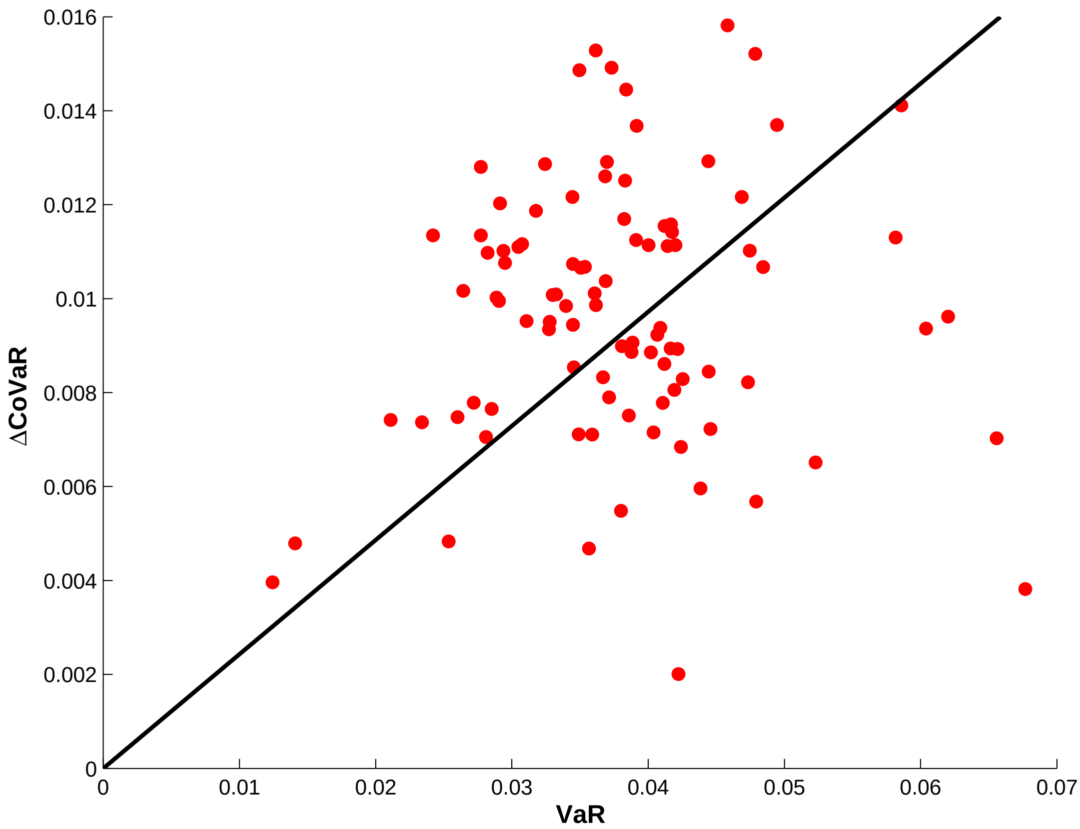
Although the SRISK is by construction a function of the MES, it is much less sensitive to beta. Unlike for MES-beta (top panel in Figure 2.3, 85.1% match), the matching is far from being perfect for SRISK-beta, with an average percentage of concordant pairs of 23.3%. SRISK rankings is more closely related to leverage (71.4% match on average), especially during relatively calm periods. Until the beginning of 2007, the percentage of concordant pairs was about 100%: the ranking produced by the SRISK was exactly the same as the leverage-based ranking for the top 10 SIFIs. However, this perfect concordance disappears during the crisis and the percentage of concordant pairs between SRISK and leverage falls to 20% in 2008. This difference can be explained by the increase in correlations, and consequently in the MES, observed during the crisis. Such an increase implies a modification of the weight given in the SRISK to the interconnectedness measure compared to the size of the firm. As a consequence, during the crisis, the percentage of concordance between the SRISK and beta rankings increases to reach 60% in October 2008 (second panel in Figure 2.3). On the contrary, the matching between the SRISK and the liabilities-based rankings has been close to 100% since the 2008 crisis. Consequently, the SRISK tend to identify the same SIFIs as the leverage in quiet periods and the same SIFIs as the liabilities during crisis periods.

Figure 2.4 Systemic Risk or Systematic Risk?



Notes: The scatter plot shows the strong cross-sectional link between the time-series average of the MES at 5% estimated for each institution (y-axis) and its beta (x-axis). The beta corresponds to the average of the time-varying beta β_{it}. Each point represents a financial institution and the solid line is the OLS regression line with no constant. The estimation period is from 01/03/2000 to 12/31/2010.

Figure 2.5 CoVaR is not Equivalent to VaR in the Cross-Section

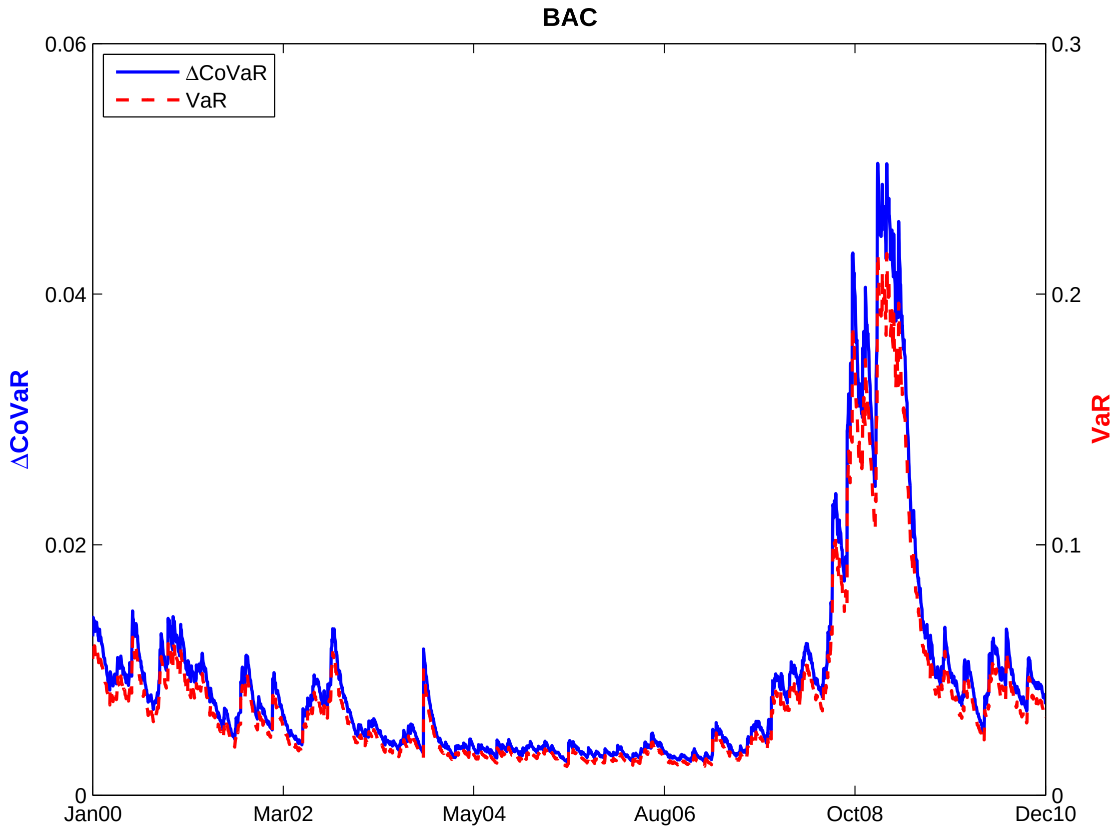


Notes: The scatter plot shows the cross-sectional link between the time-series average of the ΔCoVaR estimated for each institution (y-axis) and its VaR at 5% (x-axis). Each point represents an institution and the solid line is the OLS regression line with no constant. The estimation period is from 01/03/2000 to 12/31/2010.

As for the ΔCoVaR, we see that the ranking is pretty much orthogonal to other rankings. Of particular interest is the little overlap between the ΔCoVaR ranking and the VaR ranking (bottom panel in Figure 2.3). As already pointed out by Adrian and Brunnermeier (2011) in their Figure 1, ΔCoVaR is not equivalent to VaR. In Figure 2.5, we replicate their Figure 1 by comparing the averages $\Delta\overline{CoVaR}_i = T^{-1}\sum_{t=1}^{T}\Delta CoVaR_{it}(\alpha)$ and $\overline{VaR}_i = T^{-1}\sum_{t=1}^{T} VaR_{it}(\alpha)$ for the 94 sample firms. We also report a weak relationship between an institution's risk in isolation, measured by its VaR, and its contribution to system risk, measured by its ΔCoVaR. In that sense, ΔCoVaR is definitely not VaR.

However, the latter conclusion is more questionable for a given institution. Figure 2.6 compares the dynamics of the ΔCoVaR and VaR of Bank of America over the entire sample period. We see that the two lines match almost perfectly and there is a theoretical reason for this. Indeed, with quantile regression, ΔCoVaR is strictly proportional to the VaR (see Appendix 2.6.6). Hence, for a given financial institution, ΔCoVaR is nothing else but VaR. This result is robust to the estimation method used. Indeed, the correlation is still equal to one if we include state variables in the quantile regression. When the ΔCoVaR is estimated with a DCC model (not reported), the correlation is not one anymore but remains very high. This strong relationship between Δ CoVaR and VaR in the time series domain has some important implications. Consider a given bank that wants to lower its systemic risk score. Given the fact that the key driver of the bank's ΔCoVaR is the VaR of its stock return, the bank has to make its stock return distribution less leptokurtic and/or skewed.

Figure 2.6 CoVaR is Equivalent to VaR in Time Series



Notes: The figure displays the ΔCoVaR (solid line, left y-axis) and the 5%-VaR (dashed line, right y-axis) of Bank of America (BAC).

The main forces driving these three systemic risk measures can be summarized in a simple regression. We consider for each systemic risk measure a single-factor model in which the measure is successively explained by the market capitalization, liabilities, leverage, beta, and VaR. We consider two types of regressions: cross-sectional regressions for each of the 757 days in the sample and time-series regressions for each of the 94 sample firms. In Table 2.3, we report the average, minimum, maximum and standard deviations of the R^2 associated to the 757 or 94 regressions, respectively. The sample period covers 2008-2010.

In the cross-sectional dimension, 95% of the variance of the MES of the firms is explained by the beta. This result confirms our previous findings about the similarities

Table 2.3 Explaining Systemic Risk Measures by Market Risk and Firm Characteristics

	Time series						Cross-section					
MES	MV	LTQ	LVG	beta	VaR	all	MV	LTQ	LVG	beta	VaR	all
average R^2	0.3210	0.1742	0.3661	0.2820	0.9510	0.9687	0.0071	0.0403	0.2591	**0.9571**	0.7968	0.9837
min R^2	0.0002	0.0000	0.0003	0.0000	0.5498	0.7610	0.0000	0.0000	0.0137	**0.7198**	0.3972	0.9433
max R^2	0.8360	0.7991	0.8305	0.9758	0.9990	0.9992	0.0452	0.1852	0.7883	**0.9946**	0.9785	0.9986
std R^2	0.2272	0.1736	0.2232	0.2410	0.0727	0.0436	0.0086	0.0416	0.1477	**0.0319**	0.1100	0.0105
	Time series						Cross-section					
SRISK	MV	LTQ	LVG	beta	VaR	all	MV	LTQ	LVG	beta	VaR	all
average R^2	0.6117	0.2533	0.4888	0.2405	0.6064	0.9373	0.3197	**0.8341**	0.1840	0.1173	0.0592	0.9932
min R^2	0.0022	0.0000	0.0001	0.0003	0.0004	0.7750	0.0085	**0.2569**	0.0110	0.0034	0.0022	0.9807
max R^2	0.9635	0.9603	0.9551	0.8215	0.9086	0.9930	0.5759	**0.9952**	0.4103	0.3331	0.2269	0.9995
std R^2	0.2428	0.2441	0.2295	0.1990	0.2189	0.0391	0.1073	**0.1279**	0.0757	0.0661	0.0445	0.0036
	Time series						Cross-section					
ΔCoVaR	MV	LTQ	LVG	beta	VaR	all	MV	LTQ	LVG	beta	VaR	all
average R^2	0.3235	0.1870	0.3642	0.2645	**1.0000**	1.0000	0.0092	0.0269	0.0725	0.3297	0.2510	0.4413
min R^2	0.0022	0.0000	0.0001	0.0000	**1.0000**	1.0000	0.0000	0.0000	0.0000	0.0001	0.0001	0.1470
max R^2	0.8478	0.7876	0.7453	0.9799	**1.0000**	1.0000	0.0594	0.2486	0.8027	0.8577	0.8763	0.9149
std R^2	0.2244	0.1766	0.2178	0.2339	**0.0000**	0.0000	0.0117	0.0430	0.1261	0.1957	0.1781	0.1760

Notes: This table presents some R^2 statistics (average, minimum, maximum, and standard deviation) obtained by regressing a systemic risk measure (respectively, MES in the upper panel, SRISK in the middle panel, and ΔCoVaR in the lower panel) on one or five (all) market risk measures or firm characteristics: market value of equity (MV), liabilities (LTQ), leverage (LVG), beta, and VaR. We consider two types of regressions: time series regressions for each of the 94 sample firms (left column) and cross-sectional regressions for each of the 757 days in the sample period (right column). Each regression is run with a constant term over an estimation period covering January 2, 2008 - December 31, 2010. Bold figures indicate the explanatory variable that leads to the highest average R^2.

in the rankings produced by the two measures. However, we can also observe that in the time series dimension, 95% of the variance of the MES is explained by the VaR. The results for the SRISK confirm that it is much highly correlated to the leverage and liabilities rather than to the beta of the firm. The average R^2 of thecross-section regressions with the liabilities is equal to 83%, whereas it is only equal to 11% for beta. As for ΔCoVaR, we get a perfect correlation in time series with the VaR of the firms, for the above-mentioned reasons. In cross-section, the average R^2 of the five models for the ΔCoVaR is relatively low (the maximum average R^2 is 32% for beta). Overall our regression results clearly indicate that each considered systemic risk measure captures one dimension only of systemic risk, and this dimension corresponds to either the market risk (VaR or beta) or the liabilities of the firm.

One could argue that the large R^2 reported in Table 2.3 (time series panel) may be the sign of a spurious regression. It is indeed well known that time series regressions of non-stationary and non-cointegrated series can lead to artificially inflated R^2. To rule out this explanation, we run all the time series regressions taking the variables in first differences and the average R^2 remain high for all three measures (average R^2 (all) is 0.9061 for MES, 0.6522 for SRISK, and 1 for ΔCoVaR). Note that the perfect correlation between VaR and ΔCoVaR is a direct consequence of the quantile regression method used to generate the ΔCoVaR (see Equation (2.66) in Appendix 2.6.6).

2.5 Conclusion

Systemic risk is one of the most elusive concepts in finance. In practice, a good risk measure for systemic risk should capture many different facets that describe the importance of a given financial institution in the financial system. For instance, the Financial Stability Board states that systemic risk score should reflect size, leverage, liquidity, interconnectedness, complexity, and substitutability. In this paper, we have studied several popular systemic risk measures that are currently used by central banks and banking regulatory agencies. Our findings indicate that these measures fall short in capturing the multifaceted nature of systemic risk. We have shown, both theoretically and empirically, that most of the variability of these three systemic measures can be captured by one market risk measure or firm characteristics.

The quest for a proper systemic risk measures is still ongoing but we have reasons to remain optimistic as more data become available, with better quality, higher frequency, and wider scope (see G20 Data Gaps Initiative, Cerutti, Claessens and McGuire, 2012). Given the very nature of systemic risk, future risk measures should combine various sources of information, including balance-sheet data and proprietary data on positions (e.g. common risk exposures à la Greenwood, Thesmar and Landier, 2012) and market data (e.g. CDS à la Giglio, 2012).

2.6 Appendices

2.6.1 Appendix: Proof of Proposition 1 (MES)

Proof. Let us consider the Cholesky decomposition of the variance-covariance matrix H_t:

$$H_t^{1/2} = \begin{pmatrix} \sigma_{mt} & 0 \\ \sigma_{it}\ \rho_{it} & \sigma_{it}\ \sqrt{1-\rho_{it}^2} \end{pmatrix} \tag{2.20}$$

Given Equation (2.10), the market and firm returns can be expressed as:

$$r_{mt} = \sigma_{mt}\ \varepsilon_{mt} \tag{2.21}$$

$$r_{it} = \sigma_{it}\ \rho_{it}\ \varepsilon_{mt}\ +\ \sigma_{it}\ \sqrt{1-\rho_{it}^2}\ \xi_{it}. \tag{2.22}$$

For any conditioning event C:

$$\begin{aligned} MES_{it}(C) &= \mathbb{E}_{t-1}\Big(r_{it} \mid r_{mt} < C\Big) \\ &= \sigma_{it}\ \rho_{it}\ \mathbb{E}_{t-1}\left(\varepsilon_{mt} \mid \varepsilon_{mt} < \frac{C}{\sigma_{mt}}\right) && (2.23) \\ &\quad + \sigma_{it}\ \sqrt{1-\rho_{it}^2}\ \mathbb{E}_{t-1}\left(\xi_{it} \mid \varepsilon_{mt} < \frac{C}{\sigma_{mt}}\right). && (2.24) \end{aligned}$$

If we assume that ξ_{it} and ε_{mt} are independent, we have:

$$MES_{it}(C) = \sigma_{it}\ \rho_{it}\ \mathbb{E}_{t-1}\left(\varepsilon_{mt} \mid \varepsilon_{mt} < \frac{C}{\sigma_{mt}}\right) \tag{2.25}$$

or equivalently:

$$MES_{it}(C) = \sigma_{it}\ \rho_{it}\ \mathbb{E}_{t-1}\Big(\varepsilon_{mt} \mid r_{mt} < C\Big). \tag{2.26}$$

Let $\beta_{it} = cov(r_{it}, r_{mt})/var(r_{mt}) = \rho_{it}\sigma_{it}/\sigma_{mt}$ denotes the time-varying beta of firm i. Combining β_{it} with Equation (2.26), we obtain:

$$\begin{aligned} MES_{it}(C) &= \beta_{it}\ \sigma_{mt}\ \mathbb{E}_{t-1}\Big(\varepsilon_{mt} \mid r_{mt} < C\Big) \\ &= \beta_{it}\ \mathbb{E}_{t-1}\Big(r_{mt} \mid r_{mt} < C\Big). && (2.27) \end{aligned}$$

The MES is expressed as the product between the time-varying beta and the truncated expectation of the market return for any given threshold C. By definition, the expected shortfall of the market return $ES_{mt}(\alpha)$ corresponds to the truncated expectation of the market return for a given threshold equal to the conditional VaR (Jorion, 2007), $C = VaR_{mt}(\alpha)$:

$$ES_{mt}(\alpha) = \mathbb{E}_{t-1}\Big(r_{mt} \mid r_{mt} < VaR_{mt}(\alpha)\Big). \tag{2.28}$$

Then, the MES defined for the specific event $C = VaR_{mt}(\alpha)$, denoted $MES_{it}(\alpha)$, is simply expressed as the product of time-varying firm beta and expected shortfall of the market return:

$$MES_{it}(\alpha) = \beta_{it}\ ES_{mt}(\alpha). \tag{2.29}$$

□

2.6.2 Appendix: Proof of Proposition 2 (ΔCoVaR)

Proof. We consider two cases: a general case with $\rho_{it} \neq 0$ and a special case with $\rho_{it} = 0$. Given Equations (2.10) and (2.11), if $\rho_{it} \neq 0$ then the market return can be expressed as:

$$r_{mt} = \frac{\sigma_{mt}}{\sigma_{it}\rho_{it}}\, r_{it} - \frac{\sigma_{mt}\sqrt{1-\rho_{it}^2}}{\rho_{it}}\, \xi_{it}. \tag{2.30}$$

For each conditioning event form $\mathbb{C}(r_{it}) : r_{it} = C$, CoVaR is defined as follows:

$$\Pr\Big(\, r_{mt} \leq CoVaR_t^{m|r_{it}=C} \;\Big|\; r_{it} = C \Big) = \alpha \tag{2.31}$$

or equivalently:

$$\Pr\left(\xi_{it} \leq \frac{\rho_{it}}{\sigma_{mt}\sqrt{1-\rho_{it}^2}}\left(\frac{\sigma_{mt}}{\sigma_{it}\rho_{it}}C - CoVaR_t^{m|r_{it}=C}\right) \;\middle|\; r_{it} = C\right) = 1 - \alpha. \tag{2.32}$$

When the conditional mean function of ξ_{it} is linear in r_{it}, the first two conditional moments of ξ_{it} given $r_{it} = C$ can be expressed as:

$$\begin{aligned}
\mathbb{E}\Big(\, \xi_{it} \mid r_{it} = C \Big) &= \frac{\operatorname{cov}(\xi_{it}, r_{it})}{\sigma_{it}^2} \times C \\
&= \frac{\sigma_{it}\sqrt{1-\rho_{it}^2}}{\sigma_{it}^2} \times C \\
&= \frac{\sqrt{1-\rho_{it}^2}}{\sigma_{it}} \times C
\end{aligned} \tag{2.33}$$

$$\begin{aligned}
\mathbb{V}\Big(\, \xi_{it} \mid r_{it} \Big) &= \mathbb{V}(\xi_{it}) - \mathbb{V}_{r_{it}}\Big[\mathbb{E}\left(\xi_{it} \mid r_{it}\right)\Big] \\
&= \mathbb{V}(\xi_{it}) \times \left[1 - \left(\frac{\operatorname{cov}(\xi_{it}, r_{it})}{\sigma_{it}^2}\right)^2 \sigma_{it}^2\right] \\
&= 1 - \left(\frac{\sigma_{it}\sqrt{1-\rho_{it}^2}}{\sigma_{it}^2}\right)^2 \sigma_{it}^2 \\
&= \rho_{it}^2.
\end{aligned} \tag{2.34}$$

Consider $G(.)$ the conditional (location-scale) demeaned and standardized cdf of ξ_{it} such that:

$$\mathbb{E}\left[\frac{1}{\rho_{it}}\left(\xi_{it} - \frac{\sqrt{1-\rho_{it}^2}}{\sigma_{it}} \times C\right) \;\middle|\; r_{it} = C\right] = 0 \tag{2.35}$$

$$\mathbb{V}\left[\frac{1}{\rho_{it}}\left(\xi_{it} - \frac{\sqrt{1-\rho_{it}^2}}{\sigma_{it}} \times C\right) \;\middle|\; r_{it} = C\right] = 1. \tag{2.36}$$

Thus, Equation (2.32) is expressed as:

$$\frac{1}{\rho_{it}}\left[\frac{\rho_{it}}{\sigma_{mt}\sqrt{1-\rho_{it}^2}}\left(\frac{\sigma_{mt}}{\sigma_{it}\rho_{it}}\, C - CoVaR_t^{m|r_{it}=C}\right) - \frac{\sqrt{1-\rho_{it}^2}}{\sigma_{it}} \times C\right] = G^{-1}(1-\alpha).$$

By rearranging these terms, we write the general expression of the CoVaR:

$$CoVaR_t^{m|r_{it}=C} = -\sigma_{mt} \sqrt{1-\rho_{it}^2}\, G^{-1}(1-\alpha) + \frac{\rho_{it}\sigma_{mt}}{\sigma_{it}}\, C. \tag{2.37}$$

The CoVaR defined for the conditioning event $\mathbb{C}(r_{it}) : r_{it} = Median(r_{it})$, has a similar expression:

$$CoVaR_t^{m|r_{it}=Median(r_i)} = -\sigma_{mt} \sqrt{1-\rho_{it}^2}\, G^{-1}(1-\alpha) + \frac{\rho_{it}\sigma_{mt}}{\sigma_{it}}\, F^{-1}(0.5). \tag{2.38}$$

where $F(.)$ denotes the marginal cdf of the firm return. Then, for each conditioning event form $\mathbb{C}(r_{it}) : r_{it} = C$, the ΔCoVaR is defined as:

$$\begin{aligned} \Delta CoVaR_{it}(C) &= CoVaR_t^{m|r_{it}=C} - CoVaR_t^{m|r_{it}=Median(r_{it})} \\ &= \frac{\rho_{it}\sigma_{mt}}{\sigma_{it}} \times \Big[C - Median(r_{it})\Big] && (2.39) \\ &= \gamma_{it} \times \Big[C - Median(r_{it})\Big] && (2.40) \end{aligned}$$

where $\gamma_{it} = \rho_{it}\sigma_{mt}/\sigma_{it}$ denotes the time-varying linear projection coefficient of the market return on the firm return. If the marginal distribution of r_{it} is symmetric around zero, then $F^{-1}(0.5) = 0$, and we have:

$$\Delta CoVaR_{it}(C) = \frac{\rho_{it}\sigma_{mt}}{\sigma_{it}} \times C = \gamma_{it} \times C. \tag{2.41}$$

As in Adrian and Brunnermeier (2011), ΔCoVaR denoted $\Delta CoVaR_{it}(\alpha)$ and defined for a conditioning event $\mathbb{C}(r_{it}) : r_{it} = VaR_{it}(\alpha)$ is:

$$\Delta CoVaR_{it}(\alpha) = \gamma_{it} \times \Big[VaR_{it}(\alpha) - VaR_{it}(0.5)\Big] \tag{2.42}$$

or

$$\Delta CoVaR_{it}(\alpha) = \gamma_{it} \times VaR_{it}(\alpha) \tag{2.43}$$

if the marginal distribution of the firm return is symmetric around zero.

We now consider the case where $\rho_{it} = 0$ and the bivariate process becomes:

$$r_{mt} = \sigma_{mt}\, \varepsilon_{mt} \tag{2.44}$$

$$r_{it} = \sigma_{it}\, \xi_{it} \tag{2.45}$$

$$(\varepsilon_{mt},\ \xi_{it}) \sim D \tag{2.46}$$

where $\nu_t = (\varepsilon_{mt}, \xi_{it})'$ satisfies $\mathbb{E}(\nu_t) = 0$ and $\mathbb{E}(\nu_t \nu_t') = I_2$, and D denotes the bivariate distribution of the standardized innovations. It is straightforward to show that:

$$\begin{aligned} &\Pr\left(r_{mt} \leq CoVaR_t^{m|r_{it}=VaR_{it}(\alpha)} \;\Big|\; r_{it} = VaR_{it}(\alpha)\right) \\ &\qquad = \Pr\left(r_{mt} \leq CoVaR_t^{m|r_{it}=VaR_{it}(\alpha)}\right) = \alpha. \end{aligned}$$

Hence, we have $CoVaR_{it}(\alpha) = \sigma_{mt} F_m^{-1}(\alpha)$ and $\Delta CoVaR_{it}(\alpha) = 0$, where $F_m(.)$ denotes the cdf of the marginal distribution of the standardized market return. □

2.6.3 Appendix: Proof of Proposition 4 (Rankings MES-ΔCoVaR)

Proof. First, given Equation (2.15), the inequality $\Delta CoVaR_{it}(\alpha) \leq \Delta CoVaR_{jt}(\alpha)$ is then equivalent to:

$$\frac{\rho_{it}}{\sigma_{it}} \times \Big[VaR_{it}(\alpha) - VaR_{it}(0.5)\Big] \leq \frac{\rho_{jt}}{\sigma_{jt}} \times \Big[VaR_{jt}(\alpha) - VaR_{jt}(0.5)\Big]. \tag{2.47}$$

If we assume that the conditional distribution of the firm return is a location scale distribution, then $VaR_{it}(\alpha) = \sigma_{it} F_i^{-1}(\alpha)$ where $F_i^{-1}(\alpha)$ denotes the conditional α-quantile of the standardized return r_{it}/σ_{it}. The inequality becomes:

$$\rho_{it} \times \Big[F_i^{-1}(\alpha) - F_i^{-1}(0.5)\Big] \geq \rho_{jt} \times \Big[F_j^{-1}(\alpha) - F_j^{-1}(0.5)\Big]. \tag{2.48}$$

For simplicity, we assume that the two conditional distributions for firms i and j are identical, i.e. $F_i^{-1}(.) = F_j^{-1}(.) = F^{-1}(.)$. The difference $F^{-1}(\alpha) - F^{-1}(0.5)$ is typically a negative number, so the inequality $\Delta CoVaR_{it}(\alpha) \leq \Delta CoVaR_{jt}(\alpha)$ can be reduced to the simple condition $\rho_{it} \geq \rho_{jt}$.

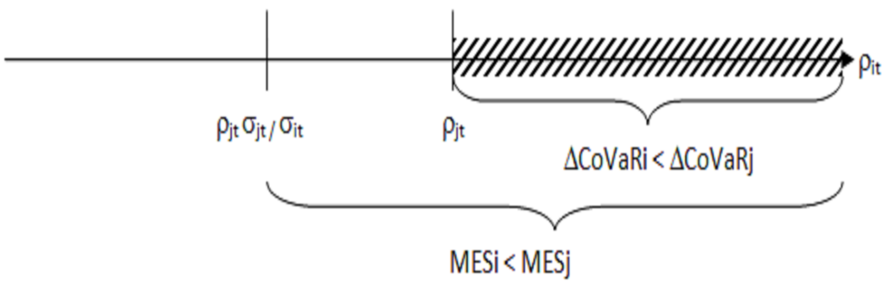
$$\Delta CoVaR_{it}(\alpha) \leq \Delta CoVaR_{jt}(\alpha) \Longleftrightarrow \rho_{it} \geq \rho_{jt}. \tag{2.49}$$

Second, the inequality $MES_{it}(\alpha) \leq MES_{jt}(\alpha)$ means that $\beta_{it} \geq \beta_{jt}$ since the system ES is negative, $ES_{mt} < 0$. Given the definition of conditional beta, this inequality is equivalent to the condition $\sigma_{it}\rho_{it} \geq \sigma_{jt}\rho_{jt}$:

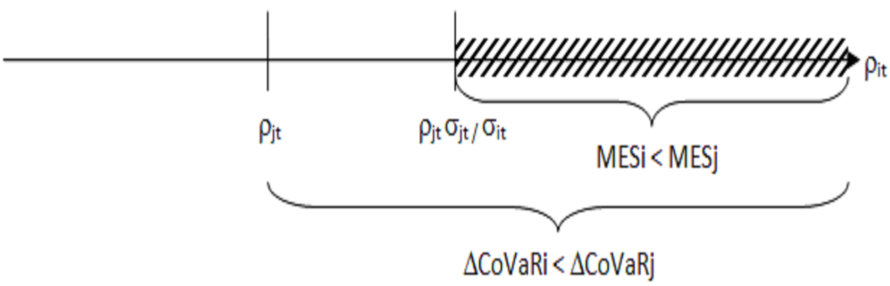
$$MES_{it}(\alpha) \leq MES_{jt}(\alpha) \Longleftrightarrow \sigma_{it}\rho_{it} \geq \sigma_{jt}\rho_{jt}. \tag{2.50}$$

We have simultaneously $MES_{it}(\alpha) \leq MES_{jt}(\alpha)$ and $\Delta CoVaR_{it}(\alpha) \leq \Delta CoVaR_{jt}(\alpha)$ when conditions (2.49) and (2.50) are satisfied. Given the relative values of the volatilities, two cases can be studied separately.

Case a: $\sigma_{it} \geq \sigma_{jt}$. Conditions (2.49) and (2.50) are satisfied if $\rho_{it} \geq \rho_{jt}$.



Case b: $\sigma_{it} < \sigma_{jt}$. Conditions (2.49) and (2.50) are satisfied if $\rho_{it} \geq \rho_{jt}\sigma_{jt}/\sigma_{it}$.



Then, the systemic risk rankings (MES and ΔCoVaR) of both financial institutions are identical when we have:

$$\rho_{it} \geq \max\left(\rho_{jt}, \frac{\rho_{jt}\sigma_{jt}}{\sigma_{it}}\right). \tag{2.51}$$

If the two conditional distributions $F_i(.)$ and $F_j(.)$ are different, but location-scale, this condition becomes:

$$\rho_{it} \geq \max\left(\rho_{jt}, \rho_{jt}\frac{[F_j^{-1}(\alpha) - F_j^{-1}(0.5)]}{[F_i^{-1}(\alpha) - F_i^{-1}(0.5)]}\right) \tag{2.52}$$

and if they are not location-scales it is:

$$\rho_{it} \geq \max\left(\rho_{jt}, \rho_{jt}\frac{\sigma_{it}[VaR_{jt}(\alpha) - VaR_{jt}(0.5)]}{\sigma_{jt}[VaR_{it}(\alpha) - VaR_{it}(0.5)]}\right). \tag{2.53}$$

$\square$

2.6.4 Appendix: Proof of Proposition 5 (Rankings SRISK-ΔCoVaR)

Proof. Given the definition of the SRISK, firm i is more risky than firm j if:

$$\left[k\ (L_{it}-1)-(1-k)\ \exp\Big(18\times\beta_{it}\times ES_{mt}(\alpha)\Big)\right]W_{it}\geq$$
$$\left[k\ (L_{jt}-1)-(1-k)\ \exp\Big(18\times\beta_{jt}\times ES_{mt}(\alpha)\Big)\right]W_{jt}\ .$$

or equivalently

$$k\ D_{it}-(1-k)\ W_{it}\ \exp\Big(18\times\beta_{it}\times ES_{mt}(\alpha)\Big)\geq$$
$$k\ D_{jt}-(1-k)\ W_{jt}\ \exp\Big(18\times\beta_{jt}\times ES_{mt}(\alpha)\Big).$$

For simplicity, we consider two firms with the same level of liabilities, $D_{it}=D_{jt}$. Then, the inequality $SRISK_{it}(\alpha)\geq SRISK_{jt}(\alpha)$ is equivalent to:

$$W_{it}\ \exp\Big(18\times\beta_{it}\times ES_{mt}(\alpha))\leq W_{jt}\ \exp\Big(18\times\beta_{jt}\times ES_{mt}(\alpha)\Big). \tag{2.54}$$

As shown in Appendix C, under some mild assumptions, we have:

$$\Delta CoVaR_{it}(\alpha)\leq\Delta CoVaR_{jt}(\alpha)\Longleftrightarrow\rho_{it}\geq\rho_{jt}. \tag{2.55}$$

The systemic risk ranking given by the SRISK and the ΔCoVaR are convergent when conditions (2.54) and (2.55) are satisfied. These conditions can be expressed as constraints on both the correlation and the market value of the riskiest firm i:

$$\rho_{it}\geq\rho_{jt}\ \text{ and }\ W_{it}\leq W_{jt}\exp\Big[18\times ES_{mt}(\alpha)\times(\beta_{jt}-\beta_{it})\Big]. \tag{2.56}$$

□

2.6.5 Appendix: Dataset

Tickers and Company Names by Industry Groups

Depositories (29)		Insurance (32)	
BAC	Bank of America	ABK	Ambac Financial Group
BBT	BB&T	AET	Aetna
BK	Bank of New York Mellon	AFL	AFLAC
C	Citigroup	AIG	American International Group
CBH	Commerce Bancorp	AIZ	Assurant
CMA	Comerica Inc.	ALL	Allstate Corp.
HBAN	Huntington Bancshares	AOC	Aon Corp.
HCBK	Hudson City Bancorp	WRB	W.R. Berkley Corp.
JPM	JP Morgan Chase	BRK	Berkshire Hathaway
KEY	Keycorp	CB	Chubb Corp.
MI	Marshall & Ilsley	CFC	Countrywide Financial
MTB	M&T Bank Corp.	CI	CIGNA Corp.
NCC	National City Corp.	CINF	Cincinnati Financial Corp.
NTRS	Northern Trust	CNA	CNA Financial Corp.
NYB	New York Community Bancorp	CVH	Coventry Health Care
PBCT	Peoples United Financial	FNF	Fidelity National Financial
PNC	PNC Financial Services	GNW	Genworth Financial
RF	Regions Financial	HIG	Hartford Financial Group
SNV	Synovus Financial	HNT	Health Net
SOV	Sovereign Bancorp	HUM	Humana
STI	Suntrust Banks	LNC	Lincoln National
STT	State Street	MBI	MBIA
UB	Unionbancal Corp.	MET	MetLife
USB	US Bancorp	MMC	Marsh & McLennan
WB	Wachovia	PFG	Principal Financial Group
WFC	Wells Fargo & Co	PGR	Progressive
WM	Washington Mutual	PRU	Prudential Financial
WU	Western Union	SAF	Safeco
ZION	Zions	TMK	Torchmark
		TRV	Travelers
		UNH	UnitedHealth Group
		UNM	Unum Group
Broker-Dealers (10)		**Others (23)**	
AGE	A.G. Edwards	ACAS	American Capital
BSC	Bear Stearns	AMP	Ameriprise Financial
ETFC	E*Trade Financial	AMTD	TD Ameritrade
GS	Goldman Sachs	AXP	American Express
LEH	Lehman Brothers	BEN	Franklin Resources
MER	Merill Lynch	BLK	BlackRock
MS	Morgan Stanley	BOT	CBOT Holdings
NMX	Nymex Holdings	CBG	C.B. Richard Ellis Group
SCHW	Schwab Charles	CBSS	Compass Bancshares
TROW	T. Rowe Price	CIT	CIT Group
		CME	CME Group
		COF	Capital One Financial
		EV	Eaton Vance
		FITB	Fifth Third Bancorp
		FNM	Fannie Mae
		FRE	Freddie Mac
		HRB	H&R Block
		ICE	Intercontinental Exchange
		JNS	Janus Capital
		LM	Legg Mason
		NYX	NYSE Euronext
		SEIC	SEI Investment Company
		SLM	SLM Corp.

2.6.6 Appendix: Estimation Methods

In order to compute the MES, the SRISK and the beta for each financial institution, we implement the estimation method of Brownlees and Engle (2012) and use the model defined in Equations (2.10) and (2.11). The conditional variances σ_{it}^2 and σ_{mt}^2 are modeled according to a TGARCH specification (Rabemananjara and Zakoïan, 1993). The time-varying correlations ρ_{it} are modeled with a symmetric DCC model. We estimate the model in two steps, using Quasi Maximum Likelihood (QML). Given the estimated correlations and variances, $\widehat{\rho}_{it}$, $\widehat{\sigma}_{it}^2$ and $\widehat{\sigma}_{mt}^2$, we estimate the beta, MES and SRISK as follows:

Beta: Given the market model defined in Equations (2.10) and (2.11), the estimated time-varying beta of the firm i is:

$$\widehat{\beta}_{it} = \frac{\widehat{\rho}_{it}\;\widehat{\sigma}_{it}}{\widehat{\sigma}_{mt}}. \tag{2.57}$$

In order to asses the robustness of our results we also consider a constant beta estimated by OLS with a linear market model $r_{it} = \alpha_i + \beta_i\; r_{mt} + \varepsilon_t$.

MES and SRISK: When we allow for nonlinear dependencies between the firm and market returns, the MES can no longer be expressed as the product of the market ES and the time-varying beta of this firm. Indeed, the conditional tail expectation $\mathbb{E}_{t-1}(\xi_{it} \mid \varepsilon_{mt} < C/\sigma_{mt})$ in the expression of the MES (Equation 2.12) can differ from zero. This term captures the tail-spillover effects from the financial system to the financial institution that are not captured by the correlation. Additionally, if both marginal distributions of the standardized returns are unknown, then the conditional expectation $\mathbb{E}_{t-1}(\varepsilon_{mt} \mid \varepsilon_{mt} < C/\sigma_{mt})$ is also unknown. Consequently, both tail expectations must be estimated. To do so, we follow Brownlees and Engle (2012) and use a nonparametric kernel estimation method (Scaillet, 2005). We consider an unconditional threshold C equal to the unconditional VaR of the system.[41] Then, if the standardized innovations ε_{mt} and ξ_{it} are *i.i.d.*, the nonparametric estimates of these tail expectations are given by:

$$\widehat{\mathbb{E}}_{t-1}\Big(\varepsilon_{mt} \mid \varepsilon_{mt} < \kappa\Big) = \frac{\sum\limits_{t=1}^{T} K\left(\frac{\kappa-\varepsilon_{mt}}{h}\right)\, \varepsilon_{mt}}{\sum\limits_{t=1}^{T} K\left(\frac{\kappa-\varepsilon_{mt}}{h}\right)} \tag{2.58}$$

$$\widehat{\mathbb{E}}_{t-1}\Big(\xi_{it} \mid \varepsilon_{mt} < \kappa\Big) = \frac{\sum\limits_{t=1}^{T} K\left(\frac{\kappa-\varepsilon_{mt}}{h}\right)\, \xi_{it}}{\sum\limits_{t=1}^{T} K\left(\frac{\kappa-\varepsilon_{mt}}{h}\right)} \tag{2.59}$$

where $\kappa = VaR_m(\alpha)/\sigma_{mt}$, $K(x) = \int_{-\infty}^{x/h} k(u)\; du$, $k(u)$ is a kernel function, and h is a positive bandwidth parameter. Following Scaillet (2005), we fix the bandwidth at $T^{-1/5}$

[41] Results obtained with $C = VaR_{mt}(\alpha)$, where $VaR_{mt}(\alpha)$ denotes the conditional VaR, are similar and available upon request.

and choose the standard normal probability distribution function as a kernel function, i.e. $k(u) = \phi(u)$. The final elements needed to compute the MES are the conditional variance and correlation estimated with a GARCH-DCC model. Then, the MES is defined as:

$$\begin{aligned}\widehat{MES}_{it}\Big(VaR_m(\alpha)\Big) &= \widehat{\sigma}_{it}\ \widehat{\rho}_{it}\ \widehat{\mathbb{E}}_{t-1}\Big(\varepsilon_{mt} \mid \varepsilon_{mt} < \kappa\Big) \\ &\quad + \widehat{\sigma}_{it}\ \sqrt{1-\widehat{\rho}_{it}^2}\ \widehat{\mathbb{E}}_{t-1}\Big(\xi_{it} \mid \varepsilon_{mt} < \kappa\Big). \end{aligned} \tag{2.60}$$

The LRMES is derived from the MES by using to the approximation proposed by Acharya, Engle and Richardson (2012), $LRMES_{it} \simeq 1 - \exp(18 \times MES_{it})$. This approximation represents the firm expected loss over a six-month horizon, obtained conditionally on the market falling by more than 40% within the next six months (for more details, see Acharya, Engle and Richardson, 2012). Finally, the SRISK is obtained from the LRMES according to Equation (2.6):

$$\widehat{SRISK}_{it} = \max\Big[0\ ;\Big[k\ L_{it} - 1 + (1-k)\ \widehat{LRMES}_{it}\Big]\, W_{it}\Big] \tag{2.61}$$

where k is the prudential capital ratio (set to 8%), L_{it} is the leverage, and W_{it} is the market value of equity.

VaR: The unconditional VaR of the system return, used to define the conditioning event in the MES, is simply estimated by the empirical quantile of the past returns:

$$\widehat{VaR}_m(\alpha) = percentile\Big(\ \{r_{mt}\}_{t=1}^{T}\ , \alpha\Big). \tag{2.62}$$

The conditional VaR of firm i, used in the ΔCoVaR definition, is computed from the QML estimated conditional variances issued from the TGARCH model. If we assume that the marginal distribution of the standardized firm returns is a location-scale distribution, the conditional VaR satisfies $\widehat{VaR}_{it}(\alpha) = F_i^{-1}(\alpha)\ \widehat{\sigma}_{it}$, where $F_i(.)$ denotes the true distribution of the standardized returns r_{it}/σ_{it} and $\widehat{\sigma}_{it}^2$ is the estimated conditional variance. Because the quantile $F_i^{-1}(\alpha)$ is unknown, we estimate it by its empirical counterpart.

ΔCoVaR: For any conditioning event $\mathbb{C}(r_{it}) : r_{it} = C_t$, $\forall C_t \in \mathbb{R}$, the CoVaR satisfies:

$$\int_{-\infty}^{CoVaR_t^{m|C_t}} f_{r_i,r_m}(x, C_t)dx = \alpha \int_{-\infty}^{\infty} f_{r_i,r_m}(x, C_t)dx \tag{2.63}$$

where $f_{r_i,r_m}(x, y)$ denotes the joint distribution of (r_{it}, r_{mt}). There is no closed form for the CoVaR, but it can be estimated in various ways including a copula function, a time-varying second-order moments model, or by bootstrapping past returns. Adrian and Brunnermeier (2011) suggest to use a standard quantile regression (Koenker and Bassett, 1978) of the market return on a particular firm return for the α-quantile:

$$r_{mt} = \mu_\alpha^i + \gamma_\alpha^i\ r_{it}. \tag{2.64}$$

For a conditioning event $\mathbb{C}(r_{it}) : r_{it} = VaR_{it}(\alpha)$, where $VaR_{it}(\alpha)$ denotes the conditional VaR of the i^{th} financial institution, the CoVaR defined by:

$$\Pr\left(r_{mt} \leq CoVaR^{m|VaR_{it}(\alpha)} \;\middle|\; r_{it} = VaR_{it}(\alpha)\right) = \alpha \tag{2.65}$$

is estimated by $\widehat{CoVaR}^{m|VaR_{it}(\alpha)} = \widehat{\mu}_{\alpha}^{i} + \widehat{\gamma}_{\alpha}^{i} \widehat{VaR}_{it}(\alpha)$, where $\widehat{\mu}_{\alpha}^{i}$ and $\widehat{\gamma}_{\alpha}^{i}$ denote the estimated parameters of the quantile regression. A similar result is obtained for the CoVaR defined for the median state of the institution, $\widehat{CoVaR}_t^{m|Median(r_i)} = \widehat{\mu}_{\alpha}^{i} + \widehat{\gamma}_{\alpha}^{i} \widehat{VaR}_{it}(0.5)$. Then, by definition, the ΔCoVaR is equal to:

$$\Delta\widehat{CoVa}R_{it}(\alpha) = \widehat{\gamma}_{\alpha}^{i} \;\left[\widehat{VaR}_{it}(\alpha) - \widehat{VaR}_{it}(0.5)\right]. \tag{2.66}$$

In order to assess the robustness of our results, we consider two alternative estimators of the CoVaR (not presented). The first one is based on an augmented quantile regression:

$$r_{mt} = \mu_{\alpha}^{i} + \gamma_{\alpha}^{i} \; r_{it} + \psi_{\alpha}^{i} \; M_{t-1} \tag{2.67}$$

where M_{t-1} denotes a vector of lagged state variables as in Adrian and Brunnermeier (2011). The second estimator is based on a GARCH-DCC model: the ΔCoVaR is obtained from the estimated time-varying second-order moments. Given Equations (2.10) and (2.11), the estimated DCC-ΔCoVaR is defined as:

$$\Delta\widehat{CoVa}R_{it}(\alpha) = \widehat{\gamma}_{it} \;\left[\widehat{VaR}_{it}(\alpha) - \widehat{VaR}_{it}(0.5)\right] \tag{2.68}$$

where $\widehat{\gamma}_{it} = \widehat{\rho}_{it}\widehat{\sigma}_{mt}/\widehat{\sigma}_{it}$.

2.6.7 Appendix: Robustness Check

Table 2.4 Systemic Risk Rankings (Top 20 Firms)

Rank	MES	SRISK	ΔCoVaR
1	MBI	BAC	HRB
2	AIG	C	MI
3	MI	JPM	BEN
4	CBG	MS	CIT
5	RF	AIG	WU
6	LM	MET	AIZ
7	JNS	PRU	AXP
8	HRB	HIG	JNS
9	BAC	SLM	NYB
10	UNM	LNC	MTB
11	ACAS	GS	EV
12	STI	RF	PGR
13	ETFC	PFG	HCBK
14	AMTD	GNW	LM
15	HBAN	STI	MBI
16	SNV	MI	TROW
17	LNC	MBI	GS
18	FITB	ETFC	MMC
19	HIG	COF	BLK
20	CIT	SNV	RF

Notes: The column labeled MES displays the ranking of the top 20 financial institutions based on MES, ranked from most to least risky. The following two columns display the top 20 financial institutions based on SRISK and ΔCoVaR, respectively. The ranking is for December 31, 2010. See Appendix 2.6.5 for the list of firm names and tickers.

Chapter 3

Implied Risk Exposures[42]

We show how to reverse-engineer banks' risk disclosures, such as Value-at-Risk, to obtain an implied measure of their exposures to equity, interest rate, foreign exchange, and commodity risks. Factor Implied Risk Exposures (FIRE) are obtained by breaking down a change in risk disclosure into a market volatility component and a bank-specific risk exposure component. In a study of large US and international banks, we show that (*i*) changes in risk exposures are negatively correlated with market volatility and (*ii*) changes in risk exposures are positively correlated across banks, which is consistent with banks exhibiting commonality in trading.

3.1 Introduction

There are many reasons for financial institutions to have correlated risk exposures. First, capital regulations around the world incentivize banks to over-invest in certain favorable asset classes, such as sovereign debt. Second, banks may share superior information, and as such, follow similar investment strategies (Hirshleifer, Subrahmanyam and Titman, 1994). Third, banks have incentives to herd to maximize the likelihood of being bailed out (Acharya and Yorulmazer, 2007, 2008; Farhi and Tirole, 2012).

Correlated risks are especially problematic during financial crises. Indeed, as market volatility spikes, regulatory capital and collateral requirements tend to mechanically increase for financial institutions. In response many banks are forced to liquidate their positions, which further amplifies market volatility (Brunnermeier and Pedersen, 2009; Merrill et al., 2013). The resulting adverse feedback effects are stronger when banks have correlated risk exposures as they tend to sell the same assets at the same time (Morris and Shin, 1999; Persaud, 2000).

A traditional approach to measuring banks' risk exposures is to regress the banks' stock returns on potential risk factors (Flannery and James, 1984; Bhattacharyya and Purnanandam, 2011). Alternatively, O'Brien and Berkowitz (2006) regress the daily trading revenues of six US banks on the ten-year US Treasury rate and other market

[42] This chapter is based on Benoit, Hurlin and Pérignon (2014), forthcoming in the *Review of Finance*.

risk factors. They find that US banks exhibit high level of heterogeneity in their risk exposures, except for interest rates. More recently, some new approaches have been proposed to infer banks' exposures to interest rate risk from accounting data. Begenau, Piazzesi and Schneider (2013) use a portfolio approach to measuring banks' exposures to interest rate risk from data on loans and interest rate swaps. They show that derivatives increase banks' exposure to interest rate risk. Landier, Sraer and Thesmar (2013) show that the interest rate sensitivity of US banks' profit increases with their income gap, which is defined as the difference between assets and liabilities that mature in less than one year.

This paper proposes a new and simple way to measure risk exposures. Unlike previous papers, we do not focus on interest rate risk and consider a broader spectrum of risks, namely equity risk, interest rate risk, foreign exchange (FX) risk, and commodity price risk. Furthermore, we extract implied risk exposures of banks from their *public risk disclosures*, with special emphasis on Value-at-Risk (VaR).[43] We exploit the fact that the level of risk disclosures depends on two main factors. It first reflects current market conditions and as such, tends to rise with market volatility. A second driving force of a bank's risk disclosure, but one that is often hidden to the public eye, is the actual risk exposures of the bank. Indeed, taking over a major stock broker would lead to a higher equity VaR for the acquiring bank. Similarly, implementing a directional trading strategy on the commodity market would certainly inflate the commodity risk figures.

We show how to decompose a change in risk disclosure into a market volatility component and a bank-specific risk exposure component. The trick we use is straightforward, yet powerful. For a broad family of distributions, the VaR is defined as the product of the standard deviation of the return and the dollar amount invested (up to a constant scaling factor). Consequently, the change in VaR can either be due to a change in volatility or in the amount invested, or both. As the former two pieces of information are public information, they can be used to extract an implied measure of the latter. This framework, which we dub "Factor Implied Risk Exposure" or FIRE, allows us to answer two important questions: (*i*) How do banks adjust their risk exposures in response to volatility shocks? (*ii*) Are changes in risk exposures correlated across banks? In other words, we investigate whether banks exhibit commonality in trading and whether correlation in risk exposures strengthens when financial markets are under stress.

We assess the performance of the FIRE in an innovative way. For a large financial institution, we systematically compare the implied risk exposures given by the FIRE with statements made by the firm about its actual risk exposures in public filings. Using quarterly data between 2003Q1 and 2013Q3, we find that the changes in risk exposures estimated by FIRE and the ones disclosed by the firm always display the same sign.

[43] The VaR corresponds to a loss that should only be exceeded with a given target probability over a given time horizon (Jorion, 2007). We show in Section 3.4.1 that our methodology can also be implemented with other types of risk disclosures.

We believe that this is reassuring evidence that our method provides meaningful risk estimates. We also study by simulation the biases on the implied exposures that could be induced by model risk and estimation risk. Overall, we find that the bias in the exposures is relatively small whatever the experiment and the sample size considered.

To develop the intuition underlying our approach, we display in Table 3.1 the changes in VaR for ten large US and international banks during an episode of substantial reduction in volatility (2008Q4-2009Q4). The VaR figures have been computed by the banks with a 99% confidence level and a one-day horizon. One attractive feature of this dataset is that it includes risk figures (factor VaR) that are defined separately for each source of risk: equity, interest rate, FX, and commodity price. During this period, volatility fell across all asset classes. The actual reduction in volatility was 46% in the equity market, 43% in the fixed-income market, 39% in the FX market, and 59% in the commodity market.[44] Despite the overall drop in volatility, we identify 17 cases, out of 40, in which the VaR *increased* over the same period. One potential explanation of this puzzling result is that volatility (↓) and risk exposures (↑) moved in opposite directions and that the risk exposure effect dominated the volatility effect for some banks.

Table 3.1 Change in Factor VaR and Factor Volatility between 2008 and 2009

$\%\Delta VaR$	Equity	Interest Rate	Foreign Exchange	Commodity
Bank of America	**54**	**137**	**355**	**442**
BNP Paribas	-30	-35	-48	**25**
Citigroup	-18	-40	-62	**20**
Crédit Agricole	-56	-73	-57	**200**
Crédit Suisse	**33**	**36**	-56	**17**
Deutsche Bank	**7**	-15	-37	**10**
Goldman Sachs	**161**	-46	-42	0
JPMorgan Chase	-7	-51	-74	-12
Morgan Stanley	0	**45**	**86**	**4**
UBS	**11**	-26	-56	-40
$\%\Delta Volatility$	-46	-43	-39	-59

Notes: The source for the VaR figures are the EDGAR database for US banks and firms' websites for international banks. We use a specific implied volatility index for each risk factor. The volatility on the equity market is measured by the Chicago Board Options Exchange VIX index. The volatility on the fixed income market is measured by the Merrill Lynch MOVE index, which tracks the volatility of Treasury bond prices using implied volatility from 30-day options. The volatility on the foreign exchange market is measured by the Deutsche Bank CVIX index, an average 3-month implied volatility for all the major currency pairs. The volatility on the commodity market is measured by the Chicago Board Options Exchange OVX index, a measure of 30-day implied volatility in West Texas Intermediate crude oil prices. Bold figures denote positive percentage changes. All sample banks report end-of-quarter daily VaR except Bank of America and BNP Paribas that report average daily VaR for each quarter. Values are expressed in percentage points.

[44] We use a specific volatility index for each risk factor (see caption of Table 3.1 for more details).

In the empirical part of the paper, we use quarterly VaR data publicly disclosed by the same ten US and international banks between 2007 and 2013. We use separate VaR figures for each major source of risk: equity, interest rate, FX, and commodity. To control for concurrent changes in volatility, we use several proxies including implied volatility and historical volatility. Our empirical analysis leads to several new findings on the risk-taking behavior of banks. First, we find that VaR covaries more frequently and more strongly with risk exposures than with market volatility. This result contrasts with the abundant literature on VaR computation in which attention is made on forecasting volatility models as the portfolios' weights are assumed to be constant. We show in this paper that when we allow for time-variation in the risk exposures, we end up with a much richer VaR dynamics. Second, we show that changes in risk exposures are negatively correlated with volatility changes, which suggests that banks curb risk when financial markets are under stress. This finding is consistent with the model of Adrian and Shin (2014) in which financial intermediaries adjust their risk exposures in reaction to changing economic conditions, in order to maintain a constant probability of default. Third, consistent with banks engaging in commonality in trading, we show that changes in risk exposures are positively correlated among banks. When contrasting periods of increasing volatility and periods of decreasing volatility, we find that the negative relationship between volatility and risk exposures, as well as commonality in risk exposures are present in all market conditions.

Our paper makes several contributions to the literature on financial risk management. First, on the methodological side, we show how to extract an implied measure of changes in banks' risk exposures from publicly available data on VaR and volatility. By doing so, we complement Taylor (2005) who shows how to generate volatility forecasts from market risk disclosures. Second, we empirically document the presence of commonality in the risk exposures of large banks. Our decomposition of the changes in risk disclosure allows us to directly test for similarities in trading positions by looking at bank risk exposures and not at trading profit-and-loss data (Berkowitz, Christoffersen and Pelletier, 2011). In two distinct studies of large US banks, Berkowitz and O'Brien (2002) and Jorion (2006) both report a moderate correlation between US banks' trading profit-and-loss, which suggests that there is significant heterogeneity in banks' risk exposures. Differently, our study of the joint dynamics of banks' risk exposures indicates that banks rebalance their trading portfolios in a correlated way.[45] Third, we contribute to the debate on the procyclicality of regulatory capital. We report a negative correlation between market volatility and risk exposures, which suggests that banks actively manage their risk exposures according to

[45]Our empirical analysis can be seen as a test of the regulation-induced herding effects of banks put forward by Morris and Shin (1999) and Persaud (2000), among others. Their argument is that a rise in market volatility increases the VaR of banks and triggers concurrent asset sales from banks, which in turn increases volatility further as well as banks' VaR, etc. Overall our empirical findings are consistent with regulation-induced herding.

market conditions. This contrarian risk-taking behavior can be seen as an attempt to damper the procyclicality of bank regulatory capital. Fourth, as our methodology relies on a certain degree of commonality in volatility across the assets within a given asset class, we show that the factor structure recently documented by Herskovic et al. (2014) for the volatility of equity is persistent across asset classes.

Our study is also related to the theory on the propagation of financial shocks. In their general-equilibrium model, Pavlova and Rigobon (2008) show that portfolio constraints, such as VaR constraints, can increase the comovement of the stock prices. While in their framework, only one agent is constrained in his portfolio choice, we consider a situation in which many financial institutions may be forced to curb their positions due to the tightening of their constraints. Furthermore, as banks tend to rebalance their risk exposures at the same time and in the same direction after a shock, our study provides empirical evidence in support of the theoretical predictions of Danielsson, Shin, and Zigrand (2004), which state that VaR constraints can exacerbate shocks further.

We envision the FIRE methodology to be used by both regulators and practitioners. For instance, banking regulators could use FIRE as a way to detect the build-up of excessive risk concentration or crowded trades among large financial institutions. Alternatively, FIRE could allow market participants to extract some signals from the flows of risk disclosures made by well-informed financial institutions. These signals could then be used to build investment strategies.

The outline of the paper is as follows. In Section 3.2, we present a methodology allowing us to extract information about changes in banks' risk exposures from public data. Section 3.3 presents the empirical analysis using actual VaR data for a sample of large US and international banks. We show in Section 3.4 how to extend the methodology to other types of risk disclosures and to time-varying skewness and kurtosis. Section 3.5 summarizes and concludes our study.

3.2 FIRE Methodology

3.2.1 Theory

When the distribution of the (demeaned) returns belongs to the location-scale family, the conditional VaR of an asset can be expressed as:

$$VaR_t = -\ \sigma_t\ F^{-1}(\alpha)\ W_t \tag{3.1}$$

where σ_t is the conditional volatility of the asset return, $F^{-1}(\alpha)$ is the α-quantile of the standardized return distribution, and W is the dollar amount invested in the asset (Jorion, 2007). We see that there are two factors driving the VaR in this set-up, namely the volatility and the amount invested.[46] The change in amount invested can be due to

[46] The two-dimensional nature of VaR is made clear in Goldman Sachs' 2013 10-K report (page 103): "*even if our positions included in VaR were unchanged, our VaR would increase with increasing market volatility and vice versa*".

the return of the asset or to inflow/outflow from the investor. The change in VaR is given by:

$$\begin{aligned} \Delta VaR_t &= VaR_{t+1} - VaR_t && (3.2)\\ &= -\ F^{-1}(\alpha)\Big(\sigma_{t+1}\ W_{t+1} - \sigma_t\ W_t\Big). && (3.3)\end{aligned}$$

While this relation only holds if $F^{-1}(\alpha)$ remains constant over time, we relax this assumption in Section 3.4.2. Under this assumption, the percentage change in VaR is:

$$\frac{\Delta VaR_t}{VaR_t} = \frac{-\ F^{-1}(\alpha)\Big(\sigma_{t+1}\ W_{t+1} - \sigma_t\ W_t\Big)}{-\ \sigma_t\ F^{-1}(\alpha)\ W_t} \tag{3.4}$$

or equivalently

$$1 + \%\Delta VaR_t = \Big(1 + \%\Delta\sigma_t\Big)\Big(1 + \%\Delta W_t\Big). \tag{3.5}$$

As a result, the percentage change in the dollar amount invested in the asset is:

$$\%\Delta W_t = \frac{1 + \%\Delta VaR_t}{1 + \%\Delta\sigma_t} - 1. \tag{3.6}$$

This equation is extremely useful. It allows us to infer the change in amount invested (unknown) from the change in VaR and volatility (both being observed).[47]

Although our methodology is very general, we focus in this paper on the actual risk disclosures of financial institutions. A common practice at large banks is to disclose their VaR for each risk factor, such as equity, interest rate, FX, and commodity (Pérignon and Smith, 2010; Basel Committee on Banking Supervision, 2011b). Specifically, a factor VaR indicates the maximum loss, at the $1-\alpha$ confidence level over a given horizon, that can be due to a given source of risk. For each bank i, we model the bank return on factor f, R_{ift}, as a function of the factor return, R_{ft}, and an idiosyncratic return, ε_{ift}:

$$R_{ift} = \beta_{ift}\ R_{ft} + \varepsilon_{ift}. \tag{3.7}$$

For instance, for equity, this means that the return on the bank's equity portfolio can be imperfectly correlated with the US equity market, as proxied by the S&P 500 stock index. The idea behind the one-factor structure is that we focus on a subportfolio that is predominantly affected by one major source of risk (e.g. equity portfolio, commodity portfolio). From Equation (3.7), we can express the variance of R_{ift}, σ^2_{ift}, as:

$$\sigma^2_{ift} = \beta^2_{ift}\ \sigma^2_{ft} + \sigma^2_{\varepsilon t} \tag{3.8}$$

where σ^2_{ft} is the variance of the factor return and $\sigma^2_{\varepsilon t}$ is the variance of the idiosyncratic return.[48] In that case, VaR is defined as:

$$\begin{aligned} VaR_{ift} &= -\ \sigma_{ift}\ F^{-1}_{if}(\alpha)\ W_{ift} && (3.9)\\ &= -\ \sqrt{\beta^2_{ift}\ \sigma^2_{ft} + \sigma^2_{\varepsilon t}}\ F^{-1}_{if}(\alpha)\ W_{ift} && (3.10)\end{aligned}$$

[47] With non-zero mean processes, the conditional mean of the return needs to be subtracted in Equation (3.1). However, given the short horizon considered, the variance term is much larger than the mean so that the mean can safely be ignored.

[48] Consistent with Equation (3.8), Herskovic et al. (2014) show that there exists a strong factor structure for the volatility of equities. We show in Section 3.2.5 that other asset classes also exhibit strong volatility factor structures.

and Equation (3.1) becomes:

$$VaR_{ift} = -\ \sigma_{ft}\ F_{if}^{-1}(\alpha)\ E_{ift} \tag{3.11}$$

where $F_{if}^{-1}(\alpha)$ is the α-quantile of the standardized factor return and E_{ift} is the risk exposure of firm i with respect to factor f at time t, which is defined by:

$$\begin{aligned} E_{ift} &= W_{ift}\sqrt{\beta_{ift}^2 + \frac{\sigma_{\varepsilon t}^2}{\sigma_{ft}^2}} && (3.12)\\ &\simeq W_{ift}\ \beta_{ift} \quad \text{when } \sigma_{\varepsilon t} \ll \sigma_{ft}. && (3.13)\end{aligned}$$

What this expression tells us is that there are two main ways for a bank to modify its risk exposure: first, the bank can change the size of its portfolio and second, it can modify the sensitivity of its portfolio with respect to a risk factor.[49] The change in VaR is given by:

$$\Delta VaR_{ift} = -\ F_{if}^{-1}(\alpha)\Big(\sigma_{ft+1}\ E_{ift+1} - \sigma_{ft}\ E_{ift}\Big) \tag{3.14}$$

and the percentage change in VaR is:

$$\begin{aligned} \frac{\Delta VaR_{ift}}{VaR_{ift}} &= \frac{-\ F_{if}^{-1}(\alpha)\Big(\sigma_{ft+1}\ E_{ift+1} - \sigma_{ft}\ E_{ift}\Big)}{-\ \sigma_{ft}\ F_{if}^{-1}(\alpha)\ E_{ift}} && (3.15)\\ 1 + \%\Delta VaR_{ift} &= \Big(1 + \%\Delta\sigma_{ft}\Big)\Big(1 + \%\Delta E_{ift}\Big). && (3.16)\end{aligned}$$

The percentage change in risk exposure between dates t and $t+1$ is given by:

$$\%\Delta E_{ift} = \frac{1 + \%\Delta VaR_{ift}}{1 + \%\Delta\sigma_{ft}} - 1. \tag{3.17}$$

Equation (3.17) is the key result of the FIRE methodology. It gives an expression for the changes in risk exposure as a function of the changes in VaR and in the volatility of the risk factor.

Note that the change in risk exposure given by Equation (3.17) is driven by both price and quantity effects: when prices move then the dollar amount invested automatically changes even if no active exposure changes (buys/sells) are made. To disentangle the price and quantity effects, one would need the individual VaR of all the securities or derivative contracts included in the bank portfolio. We provide some empirical evidence in Section 3.4 that suggests that commonality in risk exposure is not mainly driven by a price effect.

It is also important to notice that the FIRE methodology works with both long and short positions. For a short position, the VaR is defined by:

$$VaR_{ift} = -\ \sigma_{ift}\ F_{if}^{-1}(1-\alpha)\ E_{ift} \tag{3.18}$$

[49] If no single exposure in the portfolio accounts for more than an arbitrarily small share of the portfolio, then the variance of the portfolio return obtained when the portfolio size tends to infinity is fully determined by the variance of the common factor and $\sigma_{\varepsilon t} \ll \sigma_{ft}$ (see Gordy, 2003).

with $E_{ift} < 0$ (Giot and Laurent, 2003). In that case, the percentage change is also given by Equation (3.15) and the percentage change in risk exposure by Equation (3.17).[50]

3.2.2 The Main Assumption in the FIRE Methodology

The main assumption in the FIRE methodology is that the quantile $F^{-1}(\alpha)$ is constant through time. In the one-asset case (Equations (3.1)-(3.4)), the quantile remains constant as long as the distribution of the asset return does not change from one date to the next. In the case of a portfolio (Equations (3.9)-(3.15)), there are two sources of time variation in the quantile of the portfolio return distribution: changes in the distribution of the assets and changes in the portfolio weights. However, even when the weights are time-varying, the quantile remains constant if we consider conditional distributions for the asset returns that are closed in aggregation (e.g. normal distribution). Otherwise, the generalized FIRE presented in Section 3.4.2 has to be used in order to take into account the time variation in the quantile.

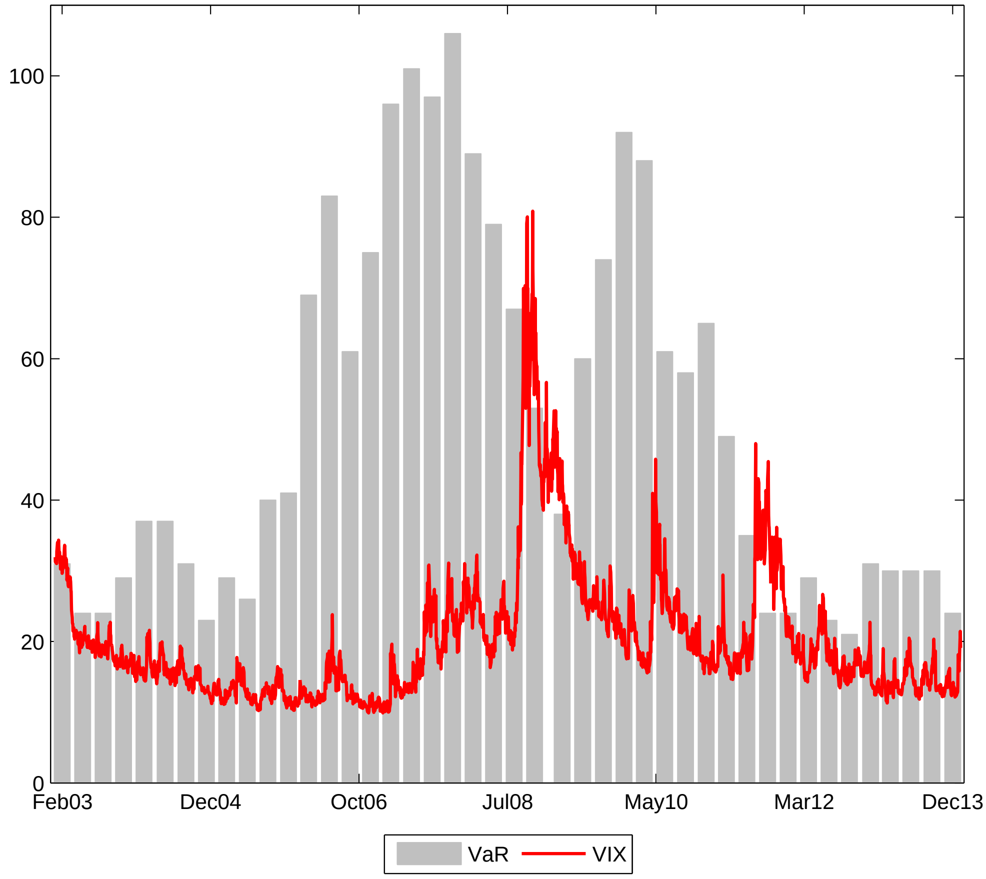
Conversely, when the portfolio contains a *large* number of assets, as it is most likely the case for the trading portfolios of the large banks studied in this paper, this distribution assumption can be relaxed. On a given date, if the number of assets tends to infinity and the bank's portfolio is sufficiently diversified, the conditional distribution of the portfolio return tends to a normal distribution, as the Central Limit Theorem applies. As a consequence, the quantile of the standardized portfolio return converges towards $\Phi^{-1}(\alpha)$ and there is no need to assume that the distributions are closed in aggregation. This limiting argument applies even if the individual returns are heterogeneously conditionally distributed (Liapounov Central Limit Theorem, see Greene, 2012, page 1082) and when the returns are weakly dependent in the cross-sectional dimension (see Bajgrowicz and Scaillet, 2012).

3.2.3 Case Study on Goldman Sachs

In order the check whether the changes in risk exposures produced by the FIRE methodology make economic sense, it would be ideal to compare the *estimated* risk exposure changes to the *actual* risk exposure changes. As the latter are typically unknown to the public, such comparison is hard to make in practice. However, we found one firm for which the comparison is possible. Indeed, Goldman Sachs makes some statements in its quarterly public filings about the recent changes in its trading portfolio. To our knowledge, Goldman Sachs is the only financial institution to make such public announcements in a systematic way over an extended period of time.

[50] If we further assume that the marginal distribution F is symmetric, then the VaR becomes $VaR_{ift} = -\sigma_{ift}\ F_f^{-1}(\alpha)\ \left|E_{ift}\right|$ for both long and short positions. Under the symmetry assumption, the FIRE methodology is robust to a change in position from a long position to a short position, and vice versa. In the symmetric case, the percentage change in risk exposure is still given by Equation (3.17).

Figure 3.1 FIRE Analysis of Goldman Sachs' Equity VaR



Notes: This figure displays the quarterly, average, 95%-confidence level, one-day ahead equity VaR of Goldman Sachs (grey bars) and VIX index (red line). The sample period covers 2003Q1-2013Q4, the VaR figures are in USD millions, and the VIX index is in percentage points. Note that the gap in VaR data immediately after November 2008 is due to the fact that the company changed its fiscal year-end from November to December.

To be able to extract the implied risk exposures, we collect quarterly equity VaR figures from all Goldman Sachs 10-Q forms between 2003Q1 and 2013Q3. These figures are one-day 95% VaRs averaged over a given quarter. Furthermore, we control for contemporaneous changes in volatility in the stock market using the VIX index. Figure 3.1 displays the quarterly values of the equity VaR along with the VIX index (both are average measures over the quarter). Eyeballing the figure shows little covariation between the VaR and the market volatility. In fact, if anything, the correlation is negative.[51] For instance, the sharp increase in volatility between 2007 and 2008 corresponds to a period of massive reduction in risk disclosure for the firm. The negative relationship between equity VaR and VIX may seem surprising at first sight, and especially if we refer to the abundant literature on tail risk in which the positive relationship between tail risk and

[51] We obtain similar pattern when we replace the VIX by the standard-deviation of daily returns on the S&P500 stock index using a three-month estimation window.

volatility is crucial (see for instance the excellent survey by Christoffersen, 2009). The fundamental positive relationship between VaR and volatility is of course true if the risk exposure remains constant through time. However, in practice, this condition is violated as trading positions can significantly vary from one quarter to the next.

For each quarter Q in year Y, we extract the change in equity risk exposure between quarter Q in year Y and quarter Q in year Y-1 using the FIRE methodology. We display the changes in equity VaR, volatility, and risk exposure in Table 3.2. We notice that the VaR increased steadily between 2003 and 2007 whereas the volatility decreased over the same period. This preliminary piece of evidence confirms that VaR is not only driven by the volatility and that changes in risk exposure are likely to play an important role in the dynamics of the risk disclosure. The relationship between the VaR and the market volatility remains negative over the entire sample period. Differently, the changes in VaR and in risk exposures are positively correlated.

As a cross-validation exercise, we contrast the risk exposure estimates with statements made by the firm about its current equity risk exposure. In each quarterly report, Goldman Sachs complements the VaR figures with information about any substantive changes in its investment strategy over the past year. For instance, in its 10-Q form dated May 2008, Goldman Sachs mentions that "*Our average daily VaR increased to $184 million for the second quarter of 2008 from $133 million for the second quarter of 2007. The increase was primarily due to higher levels of volatility [...]. These increases were partially offset by a decrease in exposures to equity prices*". Over this particular period (2008Q2 vs. 2007Q2), the FIRE methodology successfully indicates the direction of the change in risk exposures. It generates a 51% decrease in implied risk exposure for equity while, at the same time, the VIX index increased by 61%.

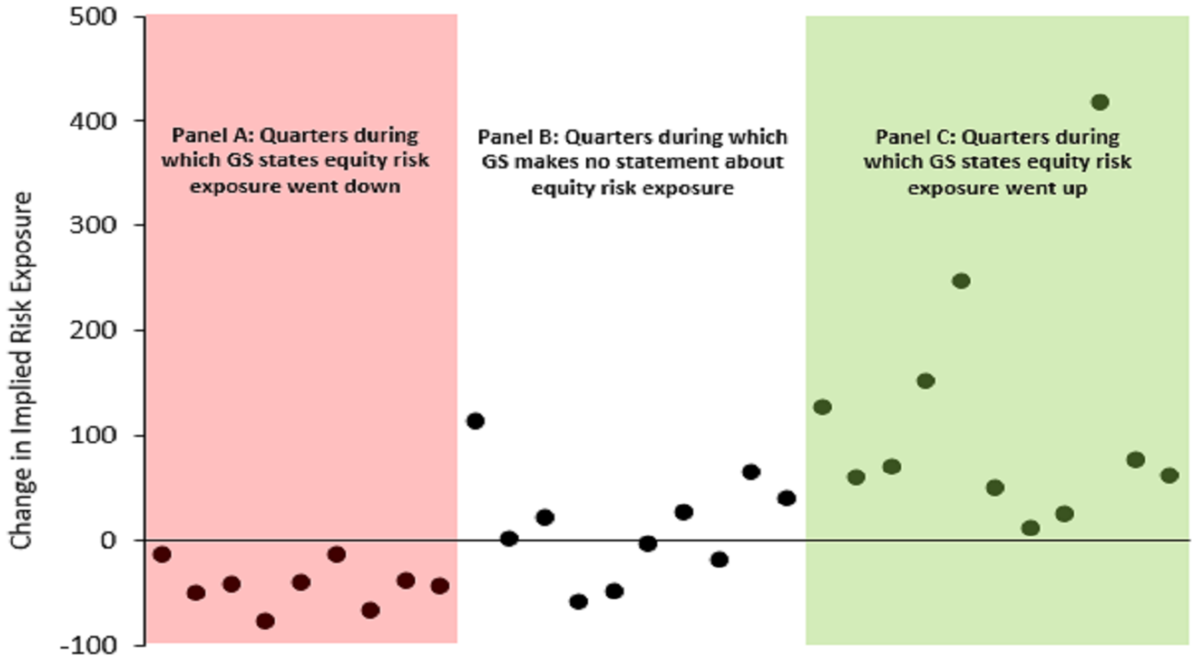
We conduct a similar analysis for all 30 quarterly reports between 2004Q1 and 2013Q3. For each quarter, we compare the change in equity risk exposure provided by the FIRE methodology with the information disclosed by the firm in its 10-Q report. As shown in Table 3.2 and Figure 3.2, we have not found a single case in which the changes in risk exposure given by FIRE and by the 10-Q forms are of opposite signs. Note that this result is not due to any major trend in risk exposures as reductions in risk exposures are almost as frequent as increases in risk disclosure in our sample (nine decreases and eleven increases). Furthermore, there are another ten quarters for which Goldman Sachs made no particular comments. Interestingly, we notice that these quarters correspond to periods during which the equity risk exposure revealed by the FIRE was more stable. We find that during high VaR change quarters ($|\Delta VaR/VaR| \geqslant 30\%$), the firm makes comments in 94.1% of the cases (16 out of 17 quarters), whereas during low VaR change quarters ($|\Delta VaR/VaR| < 30\%$), the firm makes comments in only 30.8% of the cases (4 out of 13 quarters).

Table 3.2 Changes in Equity Risk Exposure for Goldman Sachs

End of Quarter	$\%\Delta VaR_t$	$\%\Delta VIX_t$	$\%\Delta E_t$	Excerpts taken from 10-Q forms
2013Q3	43	-12	61	“increases in the equity prices [...] categories principally due to increased exposures”, p.177
2013Q2	30	-26	76	“increases in the equity prices [...] categories, principally due to increased exposures”, p.179
2013Q1	3	-26	40	[n/a]
2012Q3	-13	-47	65	[n/a]
2012Q2	-34	15	-43	“decreases in the [...] equity prices categories, principally due to reduced exposures”, p.165
2012Q1	-41	-2	-39	“decreases in the equity prices [...] categories, principally due to reduced exposures”, p.155
2011Q3	-59	26	-67	“decreases in the equity prices category, principally due to reduced exposures”, p.160
2011Q2	-43	-34	-13	“decreases across most risk categories, primarily due to reduced exposures”, p.156
2011Q1	-44	-8	-40	“The decreases in the equity prices [...] categories were primarily due to reduced exposures”, p.138
2010Q3	-22	-5	-18	[n/a]
2010Q2	2	-20	27	[n/a]
2010Q1	132	-55	417	“The increase in equity prices was primarily due to increased equity exposures”, p.119
2009Q3	10	14	-3	[n/a]
2009Q2	-24	48	-49	[n/a]
2009Q1	-57	85	-77	“The decrease in equity prices was primarily due to lower levels of exposures”, p.124
2008Q3	-31	16	-41	“The decrease in equity prices was principally due to position reductions”, p.105
2008Q2	-22	61	-51	“decrease in exposures to equity prices”, p.101
2008Q1	-7	120	-58	[n/a]
2007Q3	59	27	25	“primarily reflecting increased levels of exposure and volatility in [...] equity prices”, p.86
2007Q2	22	9	12	“primarily due to increased levels of exposure to [...] equity prices”, p.85
2007Q1	39	-7	50	“primarily due to increased levels of exposure to equity prices”, p.79
2006Q3	53	26	21	[n/a]
2006Q2	219	-8	248	“The increase was primarily due to higher levels of exposure to equity prices”, p.90
2006Q1	138	-5	151	“The increase was primarily due to higher levels of exposure to equity prices”, p.86
2005Q3	29	-24	71	“The increase was primarily due to higher levels of exposure to equity prices”, p.79
2005Q2	-30	-19	-13	“The decrease was primarily due to lower levels of exposure to equity prices”, p.75
2005Q1	-22	-23	2	[n/a]
2004Q3	29	-19	60	“The increase was primarily due to higher levels of exposure to equity prices”, p.65
2004Q2	54	-32	126	“The increase was primarily due to higher levels of exposure to equity prices”, p.65
2004Q1	19	-44	113	[n/a]

Notes: This table presents the 1-year percentage changes in equity VaR (average daily 95% VaR over the quarter), VIX, and equity risk exposures for Goldman Sachs between 2004Q1 and 2013Q3 (30 quarters). The VaR figures are from the firm's 10-Q forms, the VIX is from the CBOE website, and the changes in risk exposures are computed using the FIRE methodology. The right column of the table contains excerpts taken from the 10-Q forms of Goldman Sachs. [n/a] indicates that the 10-Q form contains no specific sentences about changes in equity risk exposures. Values are expressed in percentage points.

Figure 3.2 Empirical Performance of the FIRE Methodology



Notes: This figure displays the percentage change in implied equity risk exposure of Goldman Sachs (GS) between 2003Q1 and 2013Q3. For each quarter Q in year Y, we extract the change in equity risk exposure between quarter Q in year Y and quarter Q in year Y-1 using the FIRE methodology. The 30 quarters have been divided into three sub samples according to statements made by the firm in its 10-Q reports regarding its actual change in risk exposures. There are nine quarters during which the firm stated that its equity risk exposure did go down (Panel A), ten quarters during which the firm made no statements about its change in equity risk exposure (Panel B), and eleven quarters during which the firm stated that its equity risk exposure did go up (Panel C). In each panel, the quarters are ranked chronologically. See Table 3.2 for a list of the quarters in each panel.

We consider a series of robustness checks. First, we replace average VaR and VIX values by their end-of-quarter values. We, again, systematically compare the estimated change in risk exposures given by the FIRE methodology to actual statements made by the firm for the 30 different quarters. Second, we conduct a similar analysis using annual 10-K forms between 2004 and 2013, which leads to another 20 comparisons. In annual reports, the company compares its average (respectively year-end) equity-risk exposures in year Y to its average (respectively year-end) equity-risk exposures in year Y-1. For these 50 comparisons, there are specific comments from the firm in 27 cases. In two cases only the sign of the change in implied risk exposure does not match the company's report. However, in both cases, the implied changes in risk exposures is small (-2% and 6%), which makes misclassification more likely.

Overall, the results in this case study are encouraging. Despite the assumptions we made about the distribution and the factor structure of the return, the FIRE methodology seems to produce some risk estimates that fit well with reality. In Section 3.3, we expand the analysis to more banks and factors and investigate the comovements in risk exposures across banks.

3.2.4 Monte Carlo Simulations

In practice, both the VaR and the volatility estimates can be affected by estimation risk or model risk. For instance, banks may not correctly and promptly incorporate dynamic volatility in their VaR models. This is for instance the case when the VaR is computed by historical simulation. In this section, we study by simulation the potential biases on the FIRE that come from estimation and model risks.

To better understand the problem, we need to distinguish three elements: (*i*) the true data generating process (DGP) of the return, (*ii*) the internal model used by the bank to compute its VaR, and (*iii*) the volatility model used by the econometrician to implement the FIRE method. For simplicity, we call the latter model the FIRE model.

In our context, there are two sources of model risk. First the bank VaR model may not match with the DGP (Escanciano and Olmo, 2011). For instance, the bank computes historical simulation VaRs whereas the DGP is a GARCH(1,1). Second, the FIRE model may not match with the bank VaR model. For instance, the econometrician uses a GARCH(1,1) model whereas the bank uses historical simulation. We will see below that only the latter type of model risk can be problematic to extract risk exposures.

Moreover, estimation risk is also at play as soon as the parameters of the bank VaR model and/or of the FIRE model have to be estimated (Gouriéroux and Zakoïan, 2013). When the parameters are estimated with errors, the resulting implied exposure may also be biased. It is well known that this bias tends to disappear as the sample size increases.

The basic idea of these simulations is to assume a particular process for the changes in the bank's risk exposure and to check whether the FIRE methodology correctly estimates them. For simplicity, we consider only one asset and some discrete exposures to ease the comparison between the true and estimated exposures. On each date, the bank's exposure in the asset is assumed to change by $\Delta W_t\%$, where $\Delta W_t\%$ is drawn from a multinomial distribution on {-20%, -15%, -10%, -5%, -2%, 2%, 5%, 10%, 15%, 20%} with equal probabilities.

In all experiments, the DGP of the asset return R_t is a GARCH(1,1) process.[52] Moreover, given its exposure and a simulated sample of the returns, denoted $\{R_t^s\}_{t=1}^T$, the bank computes its VaR using its internal risk model. We consider three types of internal models: a parametric model with estimated parameters (GARCH), a parametric model with fixed parameters (RiskMetrics) and a non-parametric method (historical simulation). Finally, bank VaRs are used to estimate the implied exposure of the bank with the FIRE methodology. In our simulations, we consider three types of FIRE volatility

[52] The parameters are the following: constant = $8.5965e^{-7}$, ARCH parameter = 0.0692, and GARCH parameter = 0.9242.

models: GARCH, RiskMetrics, and historical volatility based on a rolling window of 250 days.

We consider four experiments that are presented in Panel A of Table 3.3. In the first experiment, we consider the first type of model risk in which both the bank VaR model and the FIRE model are assumed to be RiskMetrics whereas the DGP is a GARCH(1,1). Note that there is no estimation risk in this case. In the second experiment, the bank VaR model is RiskMetrics and the FIRE model is a GARCH. Since the GARCH model nests RiskMetrics, there is no model risk in this case. However, since the GARCH parameters have to be estimated, estimation risk is present. In the third experiment, there is model risk (second type) but no estimation risk. The bank VaRs are produced by historical simulation and the FIRE is based on a historical volatility obtained with the same rolling estimation window. Finally in the fourth experiment, the bank uses historical simulation to produce its VaR whereas the FIRE is based on a GARCH model, inducing both model risk and estimation risk.

In order to quantify the relative importance of model and estimation risks, we need to compare the true and implied risk exposures obtained for each simulation. This comparison is based on three statistical criteria: the percentage of matching signs, the Mean Absolute Error (MAE), and the Mean Absolute Percentage Error (MAPE). We also report the average R^2 statistics obtained by regressing the true position change on a constant and the exposure extracted with the FIRE methodology. The sample size T ranges from 250 to 2,000 observations and we run 100,000 simulations for each experiment.

The results are reported in Panels B-E of Table 3.3. Overall, we observe that the percentage of positive matching signs between the true and implied changes in exposure is always greater than 92% (91% for the percentage of negative matching signs). This result indicates that the FIRE methodology accurately predicts the direction of the change in the true risk exposure. Moreover, the bias in the exposures is relatively small whatever the experiment and the sample size considered since the R^2 is always larger than 89%.

Several other conclusions can be drawn from this series of experiments. First, risk model does not affect the performance of the FIRE except if it stems from a mismatch between the bank VaR model and the FIRE model (see experiments 1 and 2). Second, according to all evaluation criteria and sample sizes, the bias is the largest in the fourth experiment. For instance, for a sample size of 250 observations, the MAE is about 0.5% in experiments 2 and 3 whereas it is equal to 3% in the fourth experiment. This result clearly indicates that estimation risk as modeled in experiment 2, or moderate model risk as modeled in experiment 3, have limited impact on the FIRE methodology. In particular, the influence of estimation risk is very limited even in small samples ($T = 250$). Third, the magnitude of the bias decreases with sample size when there is estimation risk. For instance in the second experiment, the MAE drops from 0.65% to 0.48% when the sample size goes from 250 to 2,000 observations. When only model risk is present, the MAE does not change with sample size. In experiment 3, it is constant and equal to 0.58%.

Table 3.3 Monte Carlo Experiments

Panel A: Design of the Monte Carlo Experiments				
	Exp. 1	**Exp. 2**	**Exp. 3**	**Exp. 4**
DGP of the return	Garch(1,1)	Garch(1,1)	Garch(1,1)	Garch(1,1)
Bank VaR Model	RiskMetrics	RiskMetrics	HS	HS
FIRE Model	RiskMetrics	Garch(1,1)	HV	Garch(1,1)
Panel B: Experiment 1 - Model Risk				
Sample Size	**Matching Signs (%)**	**MAE**	**MAPE (%)**	$\mathbf{R}^2$
250	100 (100)	0.0000	0.0000	1.000
1,000	100 (100)	0.0000	0.0000	1.000
2,000	100 (100)	0.0000	0.0000	1.000
Panel C: Experiment 2 - Estimation Risk				
Sample Size	**Matching Signs (%)**	**MAE**	**MAPE (%)**	$\mathbf{R}^2$
250	99.18 (99.63)	0.0065	11.8779	0.9924
1,000	99.38 (99.83)	0.0054	9.9131	0.9948
2,000	99.51 (99.91)	0.0048	8.7629	0.9960
Panel D: Experiment 3 - Model Risk				
Sample Size	**Matching Signs (%)**	**MAE**	**MAPE (%)**	$\mathbf{R}^2$
250	99.29 (99.33)	0.0058	10.6340	0.9925
1,000	99.29 (99.33)	0.0058	10.6336	0.9923
2,000	99.29 (99.33)	0.0058	10.6332	0.9923
Panel E: Experiment 4 - Model and Estimation Risks				
Sample Size	**Matching Signs (%)**	**MAE**	**MAPE (%)**	$\mathbf{R}^2$
250	92.01 (91.71)	0.0306	56.1063	0.8978
1,000	92.03 (91.57)	0.0305	55.8513	0.8987
2,000	92.05 (91.49)	0.0304	55.6789	0.8995

Notes: This table presents the design and the results of the Monte Carlo simulations. In the four experiments, we vary (*i*) the data generating process (DGP) of the return, (*ii*) the bank VaR model, and (*iii*) the FIRE model used to extract the conditional volatility. HV denotes historical volatility and HS historical simulation. For each experiment, we report the percentage of positive and negative (in parentheses) matching signs between the true change in risk exposure and the implied change in risk exposure extracted with the FIRE methodology. We also display the average of the Moving Absolute Error (MAE) and the Moving Absolute Percentage Error (MAPE) between the changes in the true risk exposure and the implied risk exposure extracted with the FIRE methodology. Finally, we report the average R^2 statistic obtained by regressing the true position changes on a constant and the implied risk exposure. In each experiment, we vary the sample size from 250 to 2,000 observations and we use 100,000 simulations.

3.2.5 Commonality in Volatility Within an Asset Class

The FIRE methodology relies on a certain degree of commonality in volatility across the assets that belong to the same asset class, as shown in Equation (3.8). While Herskovic et al. (2014) have recently documented that equity volatility exhibit a strong factor structure, we test in Table 3.4 whether this holds true for other asset classes, such as fixed income, foreign exchange, and commodity. We follow Herskovic et al. (2014) and regress, for each asset, the asset-level volatility, σ_{ift}, on the equally-weighted average of volatility within the asset class f, $\overline{\sigma_{ft}}$:[53]

$$\sigma_{ift} = \text{intercept}_i + \text{loading}_i \ \overline{\sigma_{ft}} + e_{ift}. \tag{3.19}$$

The volatility measures are the historical standard-deviations of the daily returns, which are available for the period January 1, 1999 to June 20, 2014 (respectively, end of 2013 for equities). For equity, we extract from CRSP the daily returns of the 500 constituents of the S&P 500 stock index at the end of 2013. For fixed income, we extract from the FRED database the daily yields of all (148) securities within four categories: commercial papers (30), corporate bonds (98), Treasury bills (4), and Treasury constant maturity (16). For FX, we select the ten largest currencies based on the percentage shares of average daily turnover in April 2013 (BIS, 2013).[54] Then, we extract from Bloomberg the daily exchange rates for the 45 pairs of currencies and compute their daily returns. For commodities, we consider the constituents of the Dow Jones-UBS Commodity Index. To avoid issues due to expiration dates, we extract from Bloomberg the price of the Generic 1st month Futures for 20 components of the commodity index, as well as the S&P GSCI Kansas Wheat Index.[55]

Table 3.4 reports the cross-sectional averages of the intercept and loading coefficient estimates and of the R^2 for each asset class. In this table, we consider three frequencies: yearly in Panel A (like in Herskovic et al., 2014), quarterly in Panel B (like in the rest of this study), and monthly in Panel C. The main conclusion from all three panels is that the high degree of commonality in volatility discovered by Herskovic et al. (2014) for equities, is persistent across all main asset classes. The cross-sectional average R^2 is particularly high for equity (56.3%-66.8%), interest rate (45.1%-50.9%), foreign exchange (52.2%-59.2%), and slightly lower for commodities (29.5%-34.1%). Note that for some asset classes, the average intercept and slope coefficients differ from zero and one, respectively, because of the unbalanced panel structure of the data. We also notice that for equity,

[53] While Herskovic et al. (2014) also document commonality in idiosyncratic volatility, we only test for commonality in total volatility since the FIRE methodology is based on total volatility. In each regression, we require a minimum of 10 observations.

[54] The list of currencies, sorted in decreasing order of importance, includes the US Dollar, Euro, Japanese Yen, British Pound, Australian Dollar, Swiss Franc, Canadian Dollar, Mexican Peso, Chinese Renminbi, and New Zealand Dollar.

[55] The 20 Generic 1st month Futures are Natural Gas, WTI Crude Oil, Brent Crude Oil, Heating Oil, Live Cattle, Lean Hogs, Wheat, Corn, Soybeans, Soybean Oil, Soybean Meal, Aluminum, Copper, Zinc, Nickel, Gold, Silver, Sugar, Cotton, and Coffee.

Table 3.4 Commonality in Volatility Within an Asset Class

Panel A: Yearly Volatility Estimates

	Equity	Interest Rate	Foreign Exchange	Commodity
Loading (average)	1.006	1.007	1.000	1.000
Intercept (average)	0.028	0.031	0.000	0.000
R^2 (average univariate)	0.668	0.451	0.581	0.341
R^2 (pooled)	0.631	0.416	0.326	0.345
Observations	6,659	2,004	670	315
Number of assets	451	146	45	21

Panel B: Quarterly Volatility Estimates

	Equity	Interest Rate	Foreign Exchange	Commodity
Loading (average)	1.007	1.010	1.000	1.000
Intercept (average)	0.035	0.037	0.003	0.000
R^2 (average univariate)	0.642	0.509	0.592	0.333
R^2 (pooled)	0.612	0.463	0.354	0.309
Observations	27,347	8,353	2,766	1,302
Number of assets	485	148	45	21

Panel C: Monthly Volatility Estimates

	Equity	Interest Rate	Foreign Exchange	Commodity
Loading (average)	1.011	1.008	1.000	1.000
Intercept (average)	0.056	0.034	0.003	0.000
R^2 (average univariate)	0.563	0.499	0.522	0.295
R^2 (pooled)	0.548	0.446	0.339	0.267
Observations	82,373	25,051	8,297	3,906
Number of assets	498	148	45	21

Notes: This table presents the estimated coefficients obtained by regressing the asset-level volatility (in log) on the average volatility (in log) within the asset class. In each panel, the average volatility is defined as the equally-weighted average of securities' volatilities in a given time period: one year in Panel A, one quarter in Panel B, and one month in Panel C. The volatility measures are estimated using the historical standard-deviation of the daily returns, which are available for the period January 1, 1999 to June 20, 2014 (respectively, end of 2013 for equities). Cross-sectional averages of both loading and intercept estimates and R^2 are reported for each asset class. The pooled factor model R^2 comes from a panel regression with securities' fixed-effects and a common volatility (within estimator). The table also reports the number of observations in the pooled model as well as the number of securities used in each asset class.

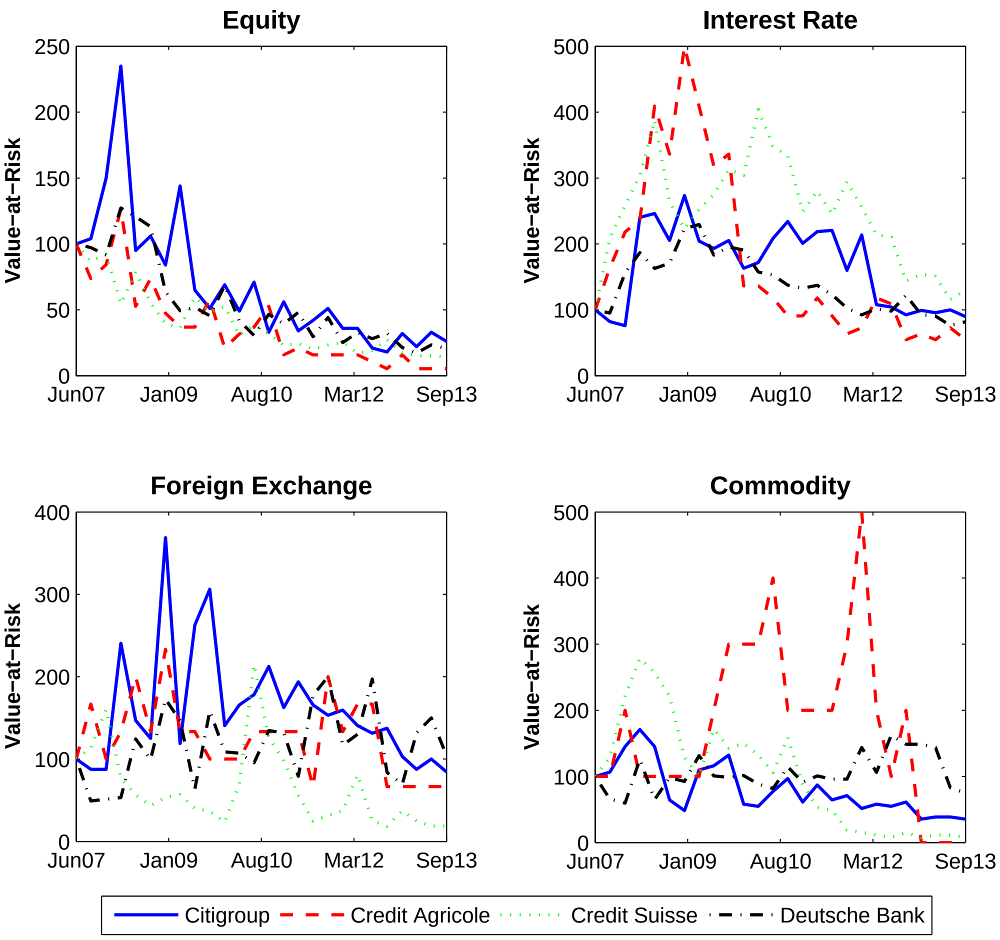
the R^2 reported in Table 3.4 with a yearly frequency tend to be higher than those in Herskovic et al. (2014), which are around 0.35. This difference is likely due to the much longer sample period (1926-2010) and much broader cross-section of assets (20,000 stocks) considered in their original study. We complement the univariate analysis by displaying the R^2 of a pooled regression obtained from a panel regression model with securities' fixed-effects (within estimator). The results indicate that our findings are robust in a panel model that imposes common loadings for all the assets. The degree of commonality in volatility remains particularly strong within equities and fixed income securities.

3.3 Changes in Risk Exposures at Large Banks

3.3.1 First Input: VaR

In this section, we study the actual changes in risk exposures at large banks before, during, and after the 2008 crisis. These risk exposure changes are extracted from the VaR of ten large US and international banks between 2007Q3 and 2013Q3 (see Appendix 3.6 for a list of the sample banks). VaR figures are publically disclosed in the quarterly and annual reports of the firms. These reports have been retrieved from the EDGAR database for US banks and from the firms' websites for international banks. The VaR figures typically have a one-day horizon and a 99% confidence level and are available on

Figure 3.3 Evolution of the Factor VaR



Notes: This figure displays the one-day ahead 99% factor VaR of Citigroup, Credit Agricole, Credit Suisse, and Deutsche Bank for four risk factors (equity, interest rate, foreign exchange, and commodity). All values are set to 100 in 2007Q2.

four different risk factors: equity, interest rate, FX, and commodity. In our tests, we use end-of-quarter VaRs for all banks, except for Bank of America and BNP Paribas for which we use average VaRs over the quarter.[56]

We first show in Figure 3.3 and Table 3.5 that the factor VaRs only exhibit some weak positive covariation across banks. Figure 3.3 displays the Value-at-Risk of four sample banks (Citigroup, Credit Agricole, Credit Suisse, and Deutsche Bank). We notice in this graph that the evolution of the VaR is quite erratic, with large changes from one quarter

Table 3.5 Correlation in Factor VaR across Banks

Average Correlation	Equity	Interest Rate	Foreign Exchange	Commodity
Bank of America	-15	14	-9	-11
BNP Paribas	49	49	4	32
Citigroup	53	47	23	36
Credit Agricole	56	57	18	8
Credit Suisse	54	49	-1	34
Deutsche Bank	59	63	3	-21
Goldman Sachs	49	55	24	35
JPMorgan Chase	12	53	22	25
Morgan Stanley	32	31	7	27
UBS	56	15	11	26
Sample Average	*41*	*43*	*10*	*19*
% of Matching Signs	Equity	Interest Rate	Foreign Exchange	Commodity
Bank of America	39	53	50	45
BNP Paribas	50	64	51	36
Citigroup	50	52	50	53
Credit Agricole	40	62	32	24
Credit Suisse	50	55	54	50
Deutsche Bank	52	59	52	42
Goldman Sachs	44	58	62	54
JPMorgan Chase	46	63	52	49
Morgan Stanley	50	55	46	46
UBS	50	52	54	37
Sample Average	*47*	*57*	*50*	*44*

Notes: The upper panel of the table presents the average correlation between the quarterly VaR of a bank and the quarterly VaR of all other sample banks for each risk factor between 2007Q3 and 2013Q3 (25 observations per bank). The lower panel reports the frequency with which the quarterly VaR of banks i and j move in the same direction (+/+ or -/-). For each bank, we compute the percentage of matching signs between the ΔVaR_{ift} of that bank and the ΔVaR_{jft} of all other sample banks, $j \neq i$. Values are expressed in percentage points.

[56] Our initial sample was the largest 25 banks in the world according to their total assets as of June 2012. We then selected all banks disclosing end-of-quarter or average VaRs for the four main risk factors (equity, interest rate, foreign exchange, and commodity). Then, we selected the longest possible sample period allowing us to get a balanced panel. See the Appendix 3.6 for more details about the VaR figures.

to the next. It is indeed not uncommon to see a VaR changing by a factor of 3 or 5 within a given year. For some risk types, there is a common trend over the sample period. For instance, the interest-rate VaR of all banks increased over 2007-08 and decreased afterwards. Similarly, there is a clear negative trend for equity risk starting at the end of 2008. Differently, there is much less comovement in the FX and commodity VaRs for these banks. We extend the analysis to all sample banks in Table 3.5 and report the average correlation between the quarterly VaR of a bank, VaR_{ift}, and the quarterly VaR of all other sample banks for each risk factor, VaR_{jft}, $j \neq i$ (upper panel). We report a positive average correlation for all four risk factors, which reflects the fact that VaR numbers are affected by some common volatility shocks. However, the magnitude of these correlations is not very high: in the 40%-45% range for equity and interest rate and less than 20% fo FX and commodity. Furthermore, we measure in the lower panel of Table 3.5 the frequency with which the VaRs of banks i and j move in the same direction. The percentage of matching signs between ΔVaR_{ift} and ΔVaR_{jft} is rather low, between 44% and 57%.

3.3.2 Second Input: Volatility

In order to control for concurrent changes in volatility, we use some factor volatility indices. These indices are extracted from options written on the different underlying factors and with maturities between one and three months. Specifically, we use the CBOE VIX index to proxy the volatility of the equity market. The volatility on the fixed income market is measured by the Merrill Lynch Move index, which tracks the implied volatility of Treasury bond prices. The volatility on the FX market is measured by the CVIX, a measure of implied volatility of major currency exchange rates. Finally, the volatility on the commodity market is measured by the OVX, a measure of implied volatility in West Texas Intermediate crude oil prices.[57] We display the evolution of the volatility of each risk factor in Figure 3.4. As expected, there is strong commonality in the volatility of these risk factors, with spikes after the Lehman collapse in October 2008 and the European sovereign-debt crisis during the summer 2011.

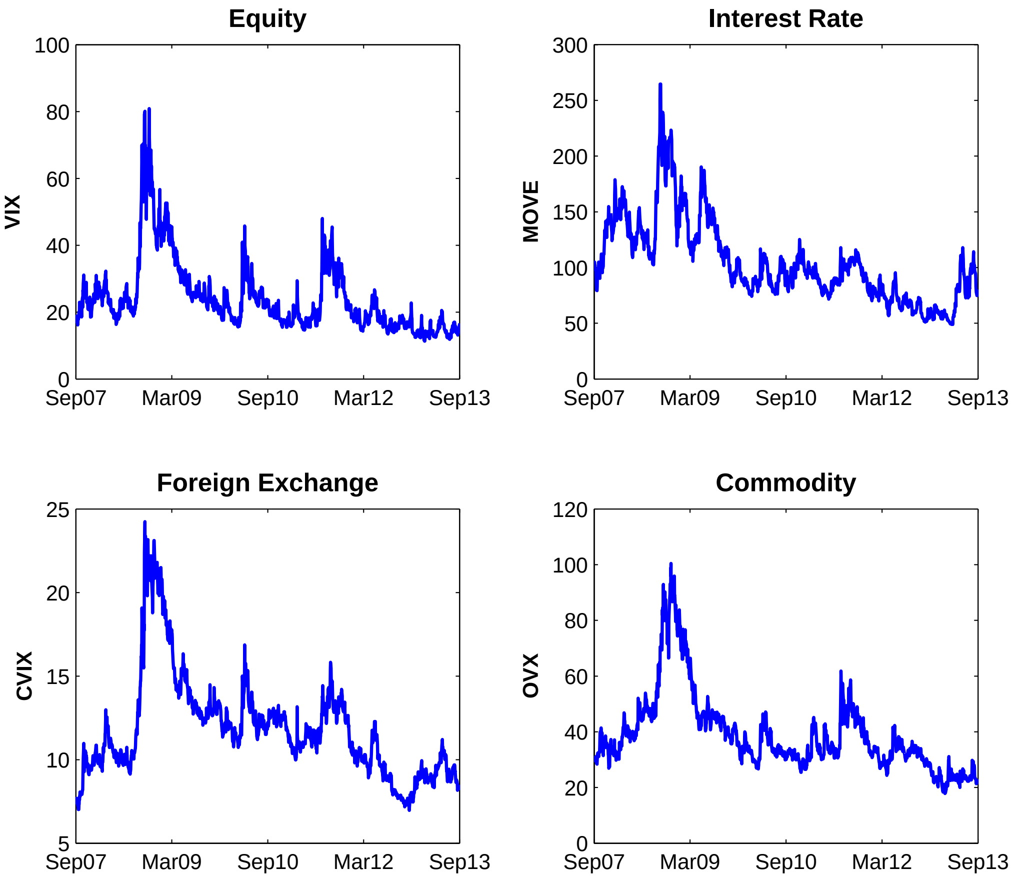
We show in Table 3.6 that the VaR and the factor volatility tend to be positively correlated for all risk factors.[58] The average correlation is lowest for commodity (16%) and highest for interest rate (53%). We also notice that this correlation is not positive for all banks. In fact, there are only five banks in our sample for which the correlation is positive for all four factors. Furthermore, when we compute the percentage of matching signs between the changes in VaR and in volatility, we find a frequency in the 40%-55% range. This finding suggests that in many occasions, the evolutions of the bank risk

[57] We use the same volatility indices as in the Risk (2010) annual VaR survey. We obtain daily data on the factor volatility indices from Bloomberg and Datastream.

[58] For banks that disclose end-of-quarter VaRs, the correlation is computed using end-of-quarter volatility. Similarly, for banks that disclose average VaRs, the correlation is computed using average volatility.

disclosures and market volatility diverge. Another implication of our preliminary set of results is that market volatility does not seem to be a dominant driving force for factor VaR.

Figure 3.4 Evolution of the Factor Volatility Indices



Notes: This figure displays the daily factor volatility for each risk factor (equity, interest rate, foreign exchange, and commodity) from 2007Q2 to 2013Q3. The volatility on the equity market is measured by the Chicago Board Options Exchange VIX index. The volatility on the fixed income market is measured by the Merrill Lynch MOVE index, which tracks the volatility of Treasury bond prices using implied volatility from 30-day options. The volatility on the foreign exchange market is measured by the Deutsche Bank CVIX index, an average 3-month implied volatility for all the major currency pairs. The volatility on the commodity market is measured by the Chicago Board Options Exchange OVX index, a measure of 30-day implied volatility in West Texas Intermediate crude oil prices.

Table 3.6 Correlation between Factor VaR and Factor Volatility

Correlation	Equity	Interest Rate	Foreign Exchange	Commodity
Bank of America	12	-9	-5	-12
BNP Paribas	52	73	43	15
Citigroup	44	49	64	20
Credit Agricole	33	79	53	10
Credit Suisse	21	52	-1	36
Deutsche Bank	32	66	37	-6
Goldman Sachs	-2	77	43	51
JPMorgan Chase	65	68	59	40
Morgan Stanley	-13	8	-8	-8
UBS	26	68	15	17
Sample Average	*27*	*53*	*30*	*16*
% of Matching Signs	Equity	Interest Rate	Foreign Exchange	Commodity
Bank of America	52	40	44	48
BNP Paribas	44	60	56	36
Citigroup	76	40	36	52
Credit Agricole	44	48	36	28
Credit Suisse	48	56	48	40
Deutsche Bank	44	48	56	44
Goldman Sachs	48	64	52	60
JPMorgan Chase	48	68	48	44
Morgan Stanley	32	52	28	48
UBS	44	60	32	36
Sample Average	*48*	*54*	*44*	*44*

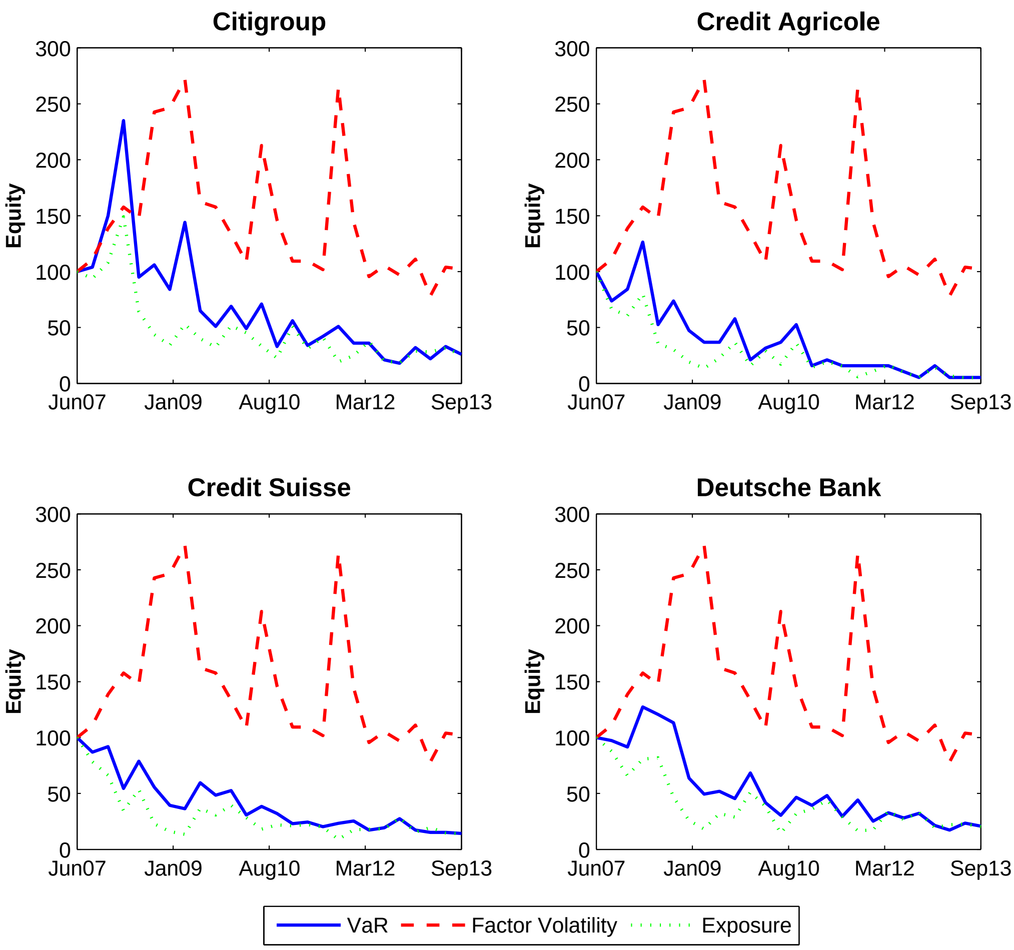
Notes: The upper panel of this table presents the correlation between the quarterly VaR of a bank and the factor volatility between 2007Q3 and 2013Q3 (25 observations per bank). The lower panel reports the frequency with which the quarterly VaR of a given bank move in the same direction as the factor volatility (+/+ or -/-). For each bank, we compute the percentage of matching signs between its ΔVaR_{ift} and the $\Delta\sigma_{ft}$. Values are expressed in percentage points.

3.3.3 Implied Risk Exposures

To formally gauge the impact of volatility and risk exposure changes on VaR, we implement the FIRE methodology that was presented in Section 3.2. For each bank/quarter, we plug the percentage change in VaR and the percentage change in volatility into Equation (3.17) to get the implied risk exposure variation for each risk factor. To have a first look at the results, we superimpose the evolution of the VaR, volatility, and implied risk exposure for equity in Figure 3.5. The message we obtain is unambiguous: the change in risk exposures is the main driving force for equity VaR.

Another important finding is that changes in risk exposure and volatility tend to move in opposite directions. We analyze the relationship between risk exposure and volatility for all factors and all banks in Table 3.7. In the upper panel of the table, we show that

Figure 3.5 Equity VaR and its Driving Forces



Notes: This figure displays the equity VaR (blue solid line), equity volatility (VIX index, red dashed line), and the implied risk exposure (green dotted line) extracted using the FIRE methodology with factor volatility indices. All values are set to 100 in 2007Q2.

the percentage changes in risk exposure and volatility are negative for virtually all firms and all factors. On average, this correlation is -53% for equity, -56% for interest rate, -25% for FX, and -56% for commodity. Moreover, as shown in the lower panel of Table 3.7, rarely do the changes in risk exposure and volatility move in the same direction.

Table 3.7 Bank Risk Exposures and Volatility

Correlation	Equity	Interest Rate	Foreign Exchange	Commodity
Bank of America	-59	-59	-33	-34
BNP Paribas	-50	-35	-27	-54
Citigroup	-34	-46	-13	-55
Credit Agricole	-35	-50	-3	-41
Credit Suisse	-59	-70	-26	-67
Deutsche Bank	-58	-78	-28	-61
Goldman Sachs	-69	-59	-22	-47
JPMorgan Chase	-21	-44	8	-79
Morgan Stanley	-77	-68	-70	-82
UBS	-65	-47	-39	-43
Sample Average	*-53*	*-56*	*-25*	*-56*
% of Matching Signs	Equity	Interest Rate	Foreign Exchange	Commodity
Bank of America	12	28	20	24
BNP Paribas	32	36	36	28
Citigroup	56	16	20	36
Credit Agricole	32	36	36	20
Credit Suisse	24	32	32	20
Deutsche Bank	24	24	32	24
Goldman Sachs	24	40	28	28
JPMorgan Chase	40	44	40	20
Morgan Stanley	12	28	20	16
UBS	28	24	24	20
Sample Average	*28*	*31*	*29*	*24*

Notes: The upper panel of this table presents the correlation between the percentage change in the quarterly risk exposure of a bank and the percentage change in quarterly factor volatility between 2007Q3 and 2013Q3 (25 observations per bank). The lower panel reports the frequency with which the quarterly risk exposure of a given bank move in the same direction as the factor volatility (+/+ or -/-). For each bank, we compute the percentage of matching signs between its ΔE_{ift} and the $\Delta\sigma_{ft}$. Values are expressed in percentage points.

Our conclusion on the negative relationship between risk exposures and market volatility is consistent with the model and empirical findings of Adrian and Shin (2014). They claim that financial firms cut back their asset exposure when the environment becomes more risky in order to maintain a constant probability of default. They show that large US banks reacted to the volatility spike in 2008 by sharply reducing their leverage. At the same time, the VaR to equity ratio barely changed.

We then move to the cross-sectional analysis of banks' risk exposures. To test whether risk exposures are correlated across banks, we report in the upper panel of Table 3.8 the average correlation between the percentage change in risk exposure of a bank, $\%\Delta E_{ift}$, and the percentage change in risk exposure of all other sample banks, $\%\Delta E_{jft}$, $j \neq i$. The lower panel of this table displays the frequency with which changes in risk exposure of banks i and j move in the same direction. The main takeaway from this table is that there is some strong commonality in bank risk exposures. Indeed, 39 out of the 40 average correlation coefficients among the changes in risk exposures are positive. Moreover, risk adjustments at two random sample banks go in the same direction between 58% and 66%

Table 3.8 Commonality in Bank Risk Exposures

Average Correlation	Equity	Interest Rate	Foreign Exchange	Commodity
Bank of America	30	35	-2	26
BNP Paribas	42	19	7	23
Citigroup	15	19	8	43
Credit Agricole	21	40	5	29
Credit Suisse	38	42	13	43
Deutsche Bank	47	44	9	36
Goldman Sachs	50	38	26	32
JPMorgan Chase	18	37	8	46
Morgan Stanley	49	33	12	40
UBS	48	36	24	23
Sample Average	*36*	*34*	*11*	*34*
% of Matching Signs	Equity	Interest Rate	Foreign Exchange	Commodity
Bank of America	64	59	52	64
BNP Paribas	68	52	55	55
Citigroup	58	63	62	65
Credit Agricole	56	63	57	65
Credit Suisse	66	63	56	71
Deutsche Bank	69	66	60	63
Goldman Sachs	68	63	62	68
JPMorgan Chase	64	66	55	68
Morgan Stanley	68	65	60	70
UBS	67	64	64	67
Sample Average	*65*	*62*	*58*	*66*

Notes: The upper panel of the table presents the average correlation between the percentage change in quarterly risk exposures of a bank, $\%\Delta E_{ift}$, and the percentage changes in quarterly risk exposures of all other sample banks, $\%\Delta E_{jft}$, $j \neq i$, between 2007Q3 and 2013Q3 (25 observations per bank). The changes in risk exposures are obtained using the FIRE methodology. The lower panel reports the frequency with which the quarterly changes in risk exposure of banks i and j move in the same direction (+/+ or -/-). Values are expressed in percentage points.

of the time, which is between 5 and 22 percentage points higher than the values for the VaR in Table 3.5.

We also model changes in risk exposures using a multivariate panel regression. Our baseline specification is:

$$\%\Delta E_{ift} = \delta_i + \delta_1 \overline{\%\Delta E_{jft}} + \delta_2 \ \%\Delta\sigma_{ft} + \delta_3 \ R_{ft} + \delta_4 \ CDS_{it} + \delta_5 \ RoE_{it} + e_{ift} \qquad (3.20)$$

where δ_i is a bank-specific intercept, $\overline{\%\Delta E_{jft}} = \sum_{i \neq j} \%\Delta E_{jft}/(N-1)$ denotes the average percentage change in banks' risk exposures, $\%\Delta\sigma_{ft}$ is the percentage change in factor volatility, R_{ft} denotes the quarterly return of the risk factor, CDS_{it} is the senior 5-year CDS of the bank, and RoE_{it} is the bank quarterly return on equity.[59] The δ_1 parameter aims to capture any commonality in risk exposures among banks whereas the δ_2 parameter measures the relationship between risk exposure and market volatility.

In our tests, we use the following indices for the four risk factors: S&P500 Index (equity), 3-Year Treasury Constant Maturity Rate (interest rate), Trade Weighted U.S. Dollar Index (FX), and Dow Jones Spot Commodity Index (commodity). The data have been retrieved from Datastream and the Federal Reserve Economic Database (FRED) and cover the period 2007Q3-2013Q3.

We present the estimation results in Table 3.9 for each risk factor (columns 1-8) and then for all risk factors stacked together (columns 9-10). We find evidence of strong commonality in risk exposures as the OLS estimated coefficients associated with other banks' risk exposures are positive and significant ($\hat{\delta}_1 > 0$). This finding holds true for all factors but the effect is particularly strong for equity and interest rate. This result is suggestive of commonality in risk exposures due to similar investment or hedging policies across banks. We also report a negative and significant relationship between risk exposure and factor volatility ($\hat{\delta}_2 < 0$), which is consistent with the univariate results in Table 3.7. We however find no evidence that banks with particularly poor performance or higher probability of default tend to take on more risk (risk shifting). We also notice that the inclusion of the control variables (R_{ft}, CDS_{it}, RoE_{it}) does not alter our conclusions on commonality in risk exposures and on the relationship between risk exposure and market volatility, with the exception of FX.

3.3.4 Robustness Checks

We consider a series of robustness checks. First, we use alternative proxies for the average change in banks' risk exposures. We replace the equally-weighted commonality proxy by a value-weighted commonality proxy (Table 3.10, Panel A) and by the first principal component of the covariance matrix of the percentage changes in risk exposures (Table 3.10, Panel B). Overall we find that our result on commonality in risk exposures remains strong and significant with all commonality proxies. Second, we change the

[59]The CDS data were retrieved from Datastream and the RoE from the banks' quarterly and annual reports.

Table 3.9 Panel Regression Analysis of Changes in Risk Exposures

	Equity		Interest Rate		Foreign Exchange		Commodity		All Factors	
	$\%\Delta E_{ift}$	$\%\Delta E_{ift}$	$\%\Delta E_{ift}$	$\%\Delta E_{ift}$	$\%\Delta E_{ift}$	$\%\Delta E_{ift}$	$\%\Delta E_{ift}$	$\%\Delta E_{ift}$	$\%\Delta E_{it}$	$\%\Delta E_{it}$
$\overline{\%\Delta E_{jft}}$	0.450***	0.323**	0.475***	0.479***	0.367*	0.360*	0.375*	0.388*	0.438***	0.435***
	(0.122)	(0.130)	(0.086)	(0.085)	(0.171)	(0.178)	(0.173)	(0.207)	(0.064)	(0.065)
$\%\Delta\sigma_{ft}$	-0.370***	-0.304***	-0.479***	-0.490***	-0.420**	-0.310	-0.652***	-0.661***	-0.437***	-0.433***
	(0.061)	(0.056)	(0.075)	(0.090)	(0.184)	(0.356)	(0.153)	(0.146)	(0.060)	(0.061)
R_{ft}		0.702		-0.013		-0.659		0.095		0.027
		(0.390)		(0.079)		(1.889)		(0.274)		(0.075)
CDS_{it}		0.0391		-0.0232		0.0513		-0.0510		0.0001
		(0.0005)		(0.0002)		(0.0008)		(0.0003)		(0.0002)
RoE_{it}		-0.0016		0.0049		-0.0019		0.0010		0.0011
		(0.0028)		(0.0040)		(0.0027)		(0.0021)		(0.0024)
Observations	250	250	250	250	250	250	250	250	1,000	1,000
R^2	0.284	0.293	0.339	0.348	0.081	0.088	0.259	0.266	0.225	0.226

Notes: This table presents the estimated coefficients and robust standard errors (in parentheses) for several regressions of the percentage changes in risk exposures for the 10 sample banks using an OLS panel regression with bank fixed effects in single factor regressions, columns (1)-(8), and with bank and factor fixed effects in the regressions aggregating all factors, columns (9)-(10). The dependent variable is the percentage change in risk exposure ($\%\Delta E_{ift}$). ***, **, * indicate that the coefficient is statistically significant at the 1%, 5% and 10% confidence level, respectively. R_{it} denotes the factor return over the quarter, CDS_{it} denotes the CDS of bank i at the beginning of the quarter, and RoE_{it} denotes the return on equity of bank i over the quarter. Each regression is run separately over an estimation period covering 2007Q3-2013Q3.

Table 3.10 Robustness Check

	Equity $\%\Delta E_{ift}$	Interest Rate $\%\Delta E_{ift}$	Foreign Exchange $\%\Delta E_{ift}$	Commodity $\%\Delta E_{ift}$	All Factors $\%\Delta E_{ift}$
	Panel A: Value-Weighted Commonality Proxy				
$\overline{\%\Delta E_{jft}}$	0.275**	0.389***	0.321**	0.383*	0.349***
	(0.089)	(0.079)	(0.128)	(0.177)	(0.059)
$\%\Delta\sigma_{ft}$	-0.472***	-0.508***	-0.507**	-0.652***	-0.501***
	(0.068)	(0.078)	(0.159)	(0.166)	(0.057)
	Panel B: First Principal Component as Commonality Proxy				
$\overline{\%\Delta E_{jft}}$	0.234***	0.225***	0.204**	0.181*	0.211***
	(0.067)	(0.039)	(0.080)	(0.099)	(0.016)
$\%\Delta\sigma_{ft}$	-0.197	-0.332***	-0.321	-0.503*	-0.300***
	(0.127)	(0.072)	(0.184)	(0.255)	(0.053)
	Panel C: Historical Volatility				
$\overline{\%\Delta E_{jft}}$	0.749***	0.630***	0.567***	0.313	0.619***
	(0.113)	(0.172)	(0.016)	(0.181)	(0.056)
$\%\Delta\sigma_{ft}$	-0.206**	-0.292**	-0.292*	-0.638***	-0.300***
	(0.070)	(0.109)	(0.142)	(0.111)	(0.053)
	Panel D: Controlling for Factor Returns				
	$\%\Delta E_{ift} - R_{ft}$	$\%\Delta E_{ift} - R_{ft}$	$\%\Delta E_{ift} - R_{ft}$	$\%\Delta E_{ift} - R_{ft}$	$\%\Delta E_{ift} - R_{ft}$
$\overline{\%\Delta E_{jft} - R_{ft}}$	0.384**	0.885***	0.378**	0.400*	0.663***
	(0.142)	(0.067)	(0.164)	(0.200)	(0.052)
$\%\Delta\sigma_{ft}$	-0.303***	-0.284**	-0.467**	-0.481***	-0.261***
	(0.055)	(0.091)	(0.192)	(0.130)	(0.053)

Notes: This table presents the estimated coefficients and robust standard errors (in parentheses) for several regressions of the percentage changes in risk exposures for the 10 sample banks using an OLS panel regression with bank fixed effects in single factor regressions, columns (1)-(4), and with bank and factor fixed effects in the regressions aggregating all factors, column 5. The dependent variable is the percentage change in risk exposure ($\%\Delta E_{ift}$ or $\%\Delta E_{ift} - R_{ft}$). ***, **, * indicate that the coefficient is statistically significant at the 1%, 5% and 10% confidence level, respectively. Each regression is run separately over an estimation period covering 2007Q3-2013Q3.

volatility proxy for the risk factors. Instead of using implied volatility indices, we compute historical volatility measures within a given quarter. Specifically, we compute the 3-month historical standard deviation of the return of the risk factor (Table 3.10, Panel C). Using these new proxies for volatility changes, we recompute the implied change in risk exposures using the FIRE method and re-run our regression. Overall, we see that our main findings are robust to this change of volatility proxy.

Several reasons can explain the commonality in risk exposures documented in Tables 3.9 and 3.10. First, banks can rebalance their trading portfolios in a correlated way because of common information. Second, they may have to curb risk at the same time because they face similar regulatory constraints. For instance, when several banks operate at their VaR limit, even a small increase in volatility would force them to unwind their positions in a correlated way. Third, the exposure of two banks with respect to a given factor can also increase because the return of this factor was positive. In order to control for the latter effect, we estimate the following panel regression:

$$\%\Delta E_{ift} - R_{ft} = \theta_i + \theta_1 \, \overline{\%\Delta E_{jft} - R_{ft}} + \theta_2 \, \%\Delta\sigma_{ft} + e_{ift} \tag{3.21}$$

where $\overline{\%\Delta E_{jft} - R_{ft}}$ is $\sum_{i\neq j}(\%\Delta E_{jft} - R_{ft})/(N-1)$. In this specification, we systematically remove the return on the factor from the change in risk exposure. Results in Panel D of Table 3.10 clearly indicate that commonality in risk exposures is not mainly due to factor returns. Indeed, the coefficient associated with other banks' changes in risk exposures (θ_1) remains positive and significant for all factors, at least at the 10% confidence level. We also notice that the strong negative relationship between volatility and risk exposure is preserved (θ_2).

Table 3.11 Subsample Analysis

	Equity	Interest Rate	Foreign Exchange	Commodity
Episode of Increase in Volatility (2007Q3-2008Q4)				
$\%\Delta Volatility$	26	23	27	22
$\%\Delta VaR$	1	26	24	3
$\%\Delta E$	-15	9	-0.1	-13
Corr($\%\Delta E_{ift}, \%\Delta E_{jft}$)	19	28	5	46
% of Matching Signs	70	52	70	69
Episode of Reduction in Volatility (2009Q1-2010Q1)				
$\%\Delta Volatility$	-15	-12	-11	-18
$\%\Delta VaR$	10	-5	14	13
$\%\Delta E$	31	16	30	41
Corr($\%\Delta E_{ift}, \%\Delta E_{jft}$)	3	58	24	23
% of Matching Signs	49	73	63	62

Notes: In this table, we contrast two subsamples. The upper (lower) panel presents the results for an episode of increase (decrease) in market volatility. In each panel, we present the average quarterly percentage change in the factor volatility index ($\%\Delta Volatility$), the average quarterly percentage change in factor VaR ($\%\Delta VaR$), the average quarterly percentage change in risk exposure ($\%\Delta E$), and the average correlation between the percentage change in risk exposures of a bank, $\%\Delta E_{ift}$, and quarterly changes risk exposure of the nine other banks, $\%\Delta E_{jft}$, $j \neq i$. Values are expressed in percentage points.

Finally, in order to test whether our conclusions remain valid in different market conditions, we split the sample into two subperiods. The first one covers 2007Q3-2008Q4 and corresponds to a period of sharp increase in market volatility (see Figure 3.4). The second subperiod, 2009Q1-2010Q1, corresponds to a period of massive reduction in market volatility. We show in Table 3.11 that the quarterly average change in factor volatility ranges between 22% and 27% in the first period and between -11% and -18% in the second period. Overall, we find that our conclusions about the dynamics of the risk exposures are persistent through the different phases of the volatility cycle. In particular, we find that the negative relationship between changes in volatility and risk exposure is a robust feature of the data. Furthermore, we report evidence of commonality in risk exposures across banks in both volatility regimes.

3.4 Extensions

3.4.1 Other Types of Risk Disclosures

So far in this study, we have only focused on one type of bank risk disclosure, namely the VaR. We now show how to infer information about risk exposures from other types of banks' risk disclosures. Under Basel III, all financial institutions with material trading activities must compute both their VaR using recent data and their *stressed* VaR (sVaR) using data from a particularly volatile period (Basel Committee on Banking Supervision, 2011b; Rossignolo, Fethi and Shaban, 2013). This measure is intended to replicate a VaR calculation that would be generated on the bank's current portfolio if the relevant market factors were experiencing a period of stress. As an example, for many portfolios, a 12-month period relating to significant losses in 2007/2008 would adequately reflect a period of such stress.

The stressed VaR is an important innovation in financial risk management. The Ernst & Young (2012) survey of financial services risk management reveals that stress testing and stressed VaR have been the top two areas of improvement in 2012: 55% of the respondents identify stressed VaR as the top area of improvement in transparency. Moreover, under Basel III, stressed VaR is included in the computation of the capital requirements for market risk, c_t:

$$c_t = \max\left\{VaR_t; m \cdot VaR_{avg}\right\} + \max\left\{sVaR_t; m_s \cdot sVaR_{avg}\right\} \tag{3.22}$$

where m and m_s are two positive multiplicative factors set by the regulators and subject to an absolute minimum of 3, and the *avg* subscript stands for an average computed over sixty business days.

We show in this section that it is possible to use the FIRE methodology with stressed, instead of standard, VaR figures. In fact, it turns out that it is much easier to learn about changes in risk exposures from stressed VaRs than it is from standard VaRs. The reason being that changes in stressed VaR are only due to changes in risk exposures, and not to changes in volatility (recall that, with stressed VaR, volatility is always measured during the same high-volatility period). We make this point formally by defining the stressed VaR as:

$$sVaR_t = -\Sigma\ F^{-1}(\alpha)\ E_t \tag{3.23}$$

where Σ denotes the conditional variance of the return measured over a particularly volatile period. We note that the variance parameter is not changing from one day to the next as it refers to a given high-volatility episode in the past. As a result, the change in stressed VaR is given by:

$$\begin{aligned} \Delta sVaR_t &= sVaR_{t+1} - sVaR_t & (3.24)\\ &= -\Sigma\ F^{-1}(\alpha)\left(E_{t+1} - E_t\right). & (3.25)\end{aligned}$$

The percentage change in VaR is:

$$\begin{aligned} \frac{\Delta sVaR_t}{sVaR_t} &= \frac{-\Sigma\ F^{-1}(\alpha)\left(E_{t+1} - E_t\right)}{-\Sigma\ F^{-1}(\alpha)\ E_t} & (3.26)\\ &= \frac{E_{t+1} - E_t}{E_t}. & (3.27)\end{aligned}$$

Then, we conclude that:

$$\%\Delta sVaR_t = \%\Delta E_t. \tag{3.28}$$

This equation shows that changes in stressed VaR only reflect changes in risk exposures. Unlike with standard VaR, changes in stressed VaR are completely immunized from volatility shocks, which greatly simplifies the analysis.

3.4.2 Generalized FIRE with Time-Varying Skewness and Kurtosis

It was shown in Section 3.2 that the α-quantile, $F^{-1}(\alpha)$, of the standardized return distribution must be constant for the FIRE to work. Obviously, if the skewness and/or the kurtosis of the conditional distribution of the returns are/is dynamic, the α-quantile may not be constant anymore and the implied exposure given by FIRE can be biased. To illustrate this, we consider a simple model in which the return is given by $R_t = \sigma_t\, \varepsilon_t$ where ε_t is *i.i.d.* with $\mathbb{E}(\varepsilon_t) = 0$ and $\mathbb{V}(\varepsilon_t) = 1$. Denote by $F_t(.)$ the cumulative density function, s_t the skewness and k_t the kurtosis of the distribution of ε_t. Using the Cornish-Fisher expansion, we know that for any $\alpha \in [0, 1]$:

$$F_t^{-1}(\alpha) = z_\alpha + \frac{s_t}{6}\left(z_\alpha^2 - 1\right) + \left(\frac{k_t - 3}{24}\right)\left(z_\alpha^3 - 3z_\alpha\right) - \frac{s_t^2}{36}\left(2z_\alpha^3 - 5z_\alpha\right) \tag{3.29}$$

where $z_\alpha = \Phi^{-1}(\alpha)$ denotes the α^{th} quantile of the standard normal distribution. Then, if s_t or k_t is dynamic, $F_t^{-1}(\alpha)$ is not constant over time. As a consequence, a generalized version of the implied exposure becomes:

$$\%\Delta W_t = \frac{1 + \%\Delta VaR_t}{(1 + \%\Delta\sigma_t)(1 + \%\Delta F_t^{-1}(\alpha))} - 1 \tag{3.30}$$

with $1 + \%\Delta F_t^{-1}(\alpha) = F_{t+1}^{-1}(\alpha)/F_t^{-1}(\alpha)$. In this case, we need to make an assumption on the dynamics of s_t and k_t. For instance, we can use the generalized skewed Student's t distribution of Hansen (1994) with ARCH-type models for the skewness and kurtosis, or the extension of Harvey and Siddique (1999, 2000).

At this point, a natural question arises. What is the cost of neglecting the dynamics of the skewness and kurtosis when extracting risk exposures? One way to answer this question is to compare the exposures given by the FIRE and a generalized version of the FIRE allowing for time-varying skewness and kurtosis. The difference in exposure depends on the value of $1 + \%\Delta F_t^{-1}(\alpha)$. From Equation (3.29), we get:

$$\begin{aligned} 1 + \%\Delta F_t^{-1}(\alpha) &= 1 + \left(\frac{z_\alpha^2 - 1}{6}\right) \%\Delta s_t + \left(\frac{z_\alpha^3 - 3z_\alpha}{24}\right) \%\Delta k_t \\ &\quad - \frac{(2z_\alpha^3 - 5z_\alpha)}{18}\, s_t\, \%\Delta s_t. \end{aligned} \tag{3.31}$$

For $\alpha = 0.01$, $s_t = -0.2$, and a range of $[-10\%,10\%]$ for both $\%\Delta s_t$ and $\%\Delta k_t$, the value of $1+\%\Delta F_t^{-1}(\alpha)$ remains between 0.9181 and 1.0819. This means that the size of the bias of the exposure induced by neglecting the dynamics of the skewness and/or kurtosis ranges from -8.92% to 7.57%. Moreover, we notice in Equation (3.31) that $\%\Delta F_t^{-1}(\alpha)$ is more sensitive with respect to the skewness than to the kurtosis. Indeed, the partial derivative with respect to the change in skewness is $(z_\alpha^2 - 1)/6 - (2z_\alpha^3 - 5z_\alpha)s_t/18 = 0.5848$ and the partial derivative with respect to the change in kurtosis is $(z_\alpha^3 - 3z_\alpha)/24 = -0.2338$.

3.5 Conclusion

Because of the G20 Data Gap Initiative, more data will have to be disclosed by financial institutions to allow policy makers and supervisors to better assess the evolution of the financial system, as well as the intervention required (Cerutti, Claessens and McGuire, 2014). However, opportunities to observe actual positions or risk exposures of banks remain extremely rare in practice (e.g. European Banking Authority's 2011 stress tests). In this paper, we present FIRE, a new technique to infer banks' risk exposures from current public disclosures; very much in the spirit of implied volatility extracted from option prices.

The performance of the FIRE turns out to be quite good in practice, despite the assumptions made to derive our key result. In the case study on Goldman Sachs, we show that the implied risk exposures are systematically in line with the statements made by the firm about its risk taking in public filings. We believe that this is reassuring evidence that our method provides meaningful estimates. In addition, we assess the performance of the FIRE by simulation by considering several situations in which model risk and estimation risk could arise. Overall, we show that, in most situations, the bias induced by model and estimation risks remains moderate.

Using a sample of large US and international banks, we find that the main driving force of bank risk disclosures is the shifts in risk exposures and not market volatility. Furthermore, we show that changes in risk exposures are negatively correlated with volatility changes, which suggests that banks aim to reduce the variability of their VaR and regulatory capital. Most importantly, we provide empirical evidence of commonality in risk exposures across banks, which supports the view that banks exhibit quite similar behavior in trading. Our empirical conclusions have some important implications for the dynamics of banks' regulatory capital. Indeed, our paper documents two sources of procyclicality in bank capital. The first one is due to the original increase in volatility while the second one arises from further volatility increases triggered by correlated risk exposures across banks, through a feedback effect.

This new framework could lead a variety of applications in the future. Implied risk exposures could, for instance, be used to study the empirical performance of the trading strategies of banks, in the spirit of the study of Agarwal et al. (2013) on hedge funds. One could also test whether some financial institutions lead their peers in terms of investment behavior. FIRE could also be used in banking supervision by complementing existing systemic risk measures (see Benoit et al., 2013, for a survey). Indeed, a situation in which a pool of large banks have a growing, common exposure to an asset class can become a serious source of concerns for banking regulators.

3.6 Appendix: VaR Data

Bank	Horizon and Confidence Level	Type of VaR Disclosed	Fiscal Year-End
Bank of America	1-day 99% VaR from 2007Q2 to 2013Q3	Average over the quarter	
BNP Paribas	1-day 99% VaR from 2007Q2 to 2013Q3	End of quarter from 2007Q2 to 2008Q1 Average over the quarter from 2008Q1 to 2013Q3	
Citigroup	1-day 99% VaR from 2007Q2 to 2013Q3	End of quarter	
Crédit Agricole	1-day 99% VaR from 2007Q2 to 2013Q3	End of quarter	
Crédit Suisse	1-day 99% VaR from 2007Q2 to 2012Q3 1-day 98% VaR from 2011Q1 to 2013Q3	End of quarter	
Deutsche Bank	1-day 99% VaR from 2007Q2 to 2013Q3	End of quarter	
Goldman Sachs	1-day 95% VaR from 2003Q1 to 2013Q3	End of quarter Average over the quarter Year end Average over the year	November until 2008, then December
JPMorgan Chase	1-day 99% VaR from 2007Q2 to 2009Q4 1-day 95% VaR from 2009Q1 to 2013Q3	End of quarter	
Morgan Stanley	1-day 95% VaR from 2007Q2 to 2013Q3	End of quarter	November until 2008, then December
UBS	10-day 99% VaR from 2007Q2 to 2009Q4 1-day 95% VaR from 2008Q4 to 2013Q3	End of quarter	

Notes: We transform 10-day VaRs into 1-day VaRs by dividing the former by $\sqrt{10}$ (square root of time rule). We also transform 95% and 98% VaRs into 99% VaRs by multiplying the former VaRs respectively by 1.4143 and 1.1327, which are equal to $\Phi^{-1}(0.99)/\Phi^{-1}(0.95)$ and $\Phi^{-1}(0.99)/\Phi^{-1}(0.98)$ (normal distribution).

Conclusion

This dissertation offers three essays which contribute to the systemic risk literature, from the Systemically Important Financial Institutions (SIFIs) identification, to the evaluation of these systemic risk measures. This work also sheds light on potential sources of systemic risk. Bank run (Diamond and Dybvig, 1983; Chari and Jagannathan, 1988) as well as bank contagion (Allen and Gale, 2000; Freixas, Parigi and Rochet, 2000) are two fundamental channels which can work together to spread a financial crisis. The latter was more prominent during the last crisis since the domino effect as well as the knock-on effect have played crucial roles.[60] The interconnectedness between financial institutions as well as the network structure are two key components of financial contagion. Elaborating precise mechanisms to explain this phenomenon is a source of intense research. However, financial institutions do not have the same degree of contagion, and accurate systemic risk measures have to be able to differentiate between contagious and non-contagious financial institutions. Thus, the identification of Systemically Important Financial Institutions (SIFIs) is a high-priority challenge to deal with systemic risk. Moreover, when contagion happens in a financial market, fire sales (Begalle et al., 2013; Duarte and Eisenbach, 2013) as well as herd behavior (Allen, Babus and Carletti, 2012) may exacerbate and propagate the financial contagion effects to generate systemic risk. Even if incentives to herd have been explained by Acharya and Yorulmazer (2007, 2008), an empirical revelation of the asset class in which the herd behavior may take place has not been achieved so far. Indeed, the level of banks' risk exposures to a given asset class is a private information. Yet this information could be useful for a regulator in order to know by how much banks are exposed to a risk factor, and whether or not these exposures are the same across banks.

The main aims of this dissertation have hence been (*i*) to propose an adjustment of the popular market-based systemic risk measures to identify domestic SIFIs, (*ii*) to theoretically and empirically evaluate these measures with respect to their ability to capture systemic risk characteristics, and (*iii*) to measure changes in risk exposures across banks, as well as their commonality, which is a potential source of systemic risk. Each of the three chapters has respectively developed one of these goals.

[60] ECB (2009) mentions that the introduction of a deposit insurance scheme has probably shut the former channel down, with the exception of the Northern Rock bank run case where the deposit insurance was partial.

Chapter 1 offers a type of User-Guide to adjust the two market-based systemic risk measures (SRIKS and ΔCoVaR) to the choice of the system. It has been highlighted that these two measures are not able to clearly distinguish between domestic and global (European) systemically important banks (D- and E-SIBs). On the contrary, the difference between the domestic SRISK and the global SRISK may produce accurate ranking to identify D-SIBs and gauge the shortage of capital that a bank may have when this bank is jointly identified as E- and D-SIBs. The main advantage of this approach is to use publicly available data on stock returns and balance sheet components to propose a policy direction to identify and determine the accurate amount of loss absorbency required for D-SIBs. To extend this work, an event study could be realized with respect to banks whose distresses have only impacted their national financial market. From the Bankia bailout in 2012 to the emergency loans to Monte Dei Paschi Di Siena issued by the Bank of Italy in 2013, examples of banks facing losses are multiple in Europe, but their local or global consequences have never been investigated. Such a survey may be an interesting tool to validate our measure to identify D-SIBs. For example, Espirito Santo was considered as the most domestically SIB in Portugal based on our methodology on December 30, 2011 and this bank has been bailed-in in August 2014.

Chapter 2 provides an accurate comparison of the major market-based systemic risk measures (MES, SES, SRISK and ΔCoVaR). Theoretically, these measures are derived in a common framework allowing to show that these measures are nonlinear combinations of standard financial risks (systematic risk, tail risk, correlation, and beta), as well as firm characteristics such as leverage and market capitalization. Conditions under which these different measures lead to similar rankings of SIFIs are also derived. Empirically, it is shown that different systemic risk measures identify different SIFIs. This empirical illustration enables the theoretical findings – that rankings based on these measures mirror rankings obtained by sorting firms on market risk or liabilities – to be confirmed. The latter result is reinforced by cross-section and time series regressions in which one-factor linear models explain most of the variability of these systemic risk estimates. The main conclusion of the chapter is that systemic risk measures fall short in capturing the multiple facets of systemic risk, and this finding has been echoed by several academic studies (Löffler and Raupauch, 2013; Tavolaro and Visnovsky, 2014; Idier, Lamé and Mésonnier, 2012). To extend this work, simple rankings based on these measures may be not accurate since the individual systemic risk contribution of two financial institutions could be not significantly different. Hurlin et al. (2013) suggest an iterative procedure to test the equality of the systemic importance of two financial institutions based on market-based measures (see also Castro and Ferrari, 2012, who provide a test of dominance for the ΔCoVaR).

Chapter 3 develops the Factor Implied Risk Exposures (FIRE) methodology to infer banks' risk exposures from current public risk disclosures, such as the Value-at-Risk (VaR). Indeed, we breakdown a change in risk disclosure into a market volatility component and a bank-specific risk exposure component. The chosen approach relies on a certain degree of commonality in volatility across assets within a given asset class, and aims at documenting the presence of such a factor structure for the volatility across four asset classes. The performance of this methodology is verified by simulations to evaluate its potential biases due to model and estimation risk. Statements made by a large financial institution about its actual risk exposures in public filings are compared with the implied risk exposures given by the FIRE methodology. Then, we empirically show that banks tend to decrease (increase) their exposures when volatility goes up (down). This negative correlation between these two components can be seen as an attempt to damper the procyclicality of bank regulatory capital. We find a positive correlation between changes in risk exposures across banks, which is consistent with literature about banks exhibiting commonality in trading and assets holding. To extend this work, additional models to explain how badly common changes in banks' risk exposures could propagate and exacerbate the financial crisis should be of high interest. Moreover, tracking this commonality over time could be a relevant tool for macroprudential purpose since we could easily identify in which factors the banks get in or out.

In this dissertation, research on systemic risk has thus focused on three main aspects. Yet systemic risk remains a promising avenue of research, notably on the aspects that are about to be presented.

First, the quantification of systemic risk is based on models and the inherent risk of those should be econometrically addressed. Danielsson et al. (2011) argue that market-based systemic risk measures contain a high degree of model risk due to their dependence to standard risk measures (VaR or ES), which are noisy riskometers. A remedy to model risk by adjusting these systemic risk measures could be proposed in the same vein that the one developed by Boucher et al. (2014) for the VaR. However, they use backtesting procedures to realize the VaR adjustment but so far, we do not have econometric tools to validate systemic risk measurement.

Second, the relevance of systemic risk measures should be empirically evaluated. Whatever the model in which they are developed, to be informative for banking regulators, systemic risk measures should link financial sector crises and macroeconomic effects. In other words, they should incorporate the dynamic interaction between the financial and real sectors. Only a few systemic risk measures of the financial system as a whole are based on this idea, such as the Default Intensity Model (DIM) proposed by Giesecke and Kim (2011), and the systemic real risk indicator (GDP-at-Risk) as well as the systemic financial risk indicator introduced by De Nicolò and Lucchetta (2010).

To evaluate individual systemic risk measures, among others, Giglio, Kelly and Pruitt (2013) evaluate these measures based on their ability to predict low quantiles of real macroeconomic aggregates. They show that, taken individually, these measures fall short to predict economic slowdown whereas an index based on those measures performs well. As a consequence, strict criteria to gauge the degree of informativeness of these systemic risk measures should be defined.

Third, financial market infrastructures are also subject to systemic risk. Most of derivative exchanges use central counterparties (CCPs). Acharya et al. (2009) have suggested that the lack of such clearing process for Credit Defaults Swaps (CDS), for instance, have significantly exacerbated the severity of the financial crisis because they were traded in bilateral transactions over-the-counter. Thus policy makers have asked that CDS be now clear through CCPs. Indeed, as highlighted by Duffie and Zhu (2011), systemic risk is well mitigated (by lowering counterparty risk) in a single CCP that clears in the same time various derivative classes. The reverse side is that CCP default becomes systemic since all clearing members will be affected at the same time.[61] In their 2012 Annual Report, the Financial Stability Oversight Council (FSOC, 2012b) designates eight CCPs as Systemically Important Financial Market Utilities (SIFMUs) due to their predominant position in a market. Identifying these SIFMUs and potential channels that are able to destabilize a CCP, such as crowded trades (Menkveld, 2014), remain attractive fields of research to pursue our investigation on systemic risk.

[61] Hills et al. (1999) describe the consequences of three failures of CCP on the financial stability.

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Résumé en français

Le risque systémique, défini au sens large comme le risque d'un effondrement global du système financier, est depuis longtemps un sujet de recherche fondamental en finance, à la fois en économie et en gestion. L'exemple typique est celui de la crise bancaire et de la grande dépression des années 1930 (voir de Bandt et Hartmann, 2002, pour une synthèse des travaux majeurs de l'époque sur le risque systémique). Mais c'est sans conteste la crise financière de 2007-2008 qui a conduit à profondément renouveler l'intérêt des régulateurs et des chercheurs pour cette notion de risque systémique, notamment dans la perspective de la mise en place d'une régulation macroprudentielle.

Cette thèse s'inscrit dans ce débat sur le risque systémique et la supervision bancaire, et affiche trois objectifs principaux : (*i*) évaluer les principales mesures du risque systémique, (*ii*) les appliquer et les évaluer d'un point de vue réglementaire et (*iii*) proposer des pistes d'amélioration de ces mesures ou de nouvelles mesures. En effet, si le concept de risque systémique est relativement clair, le problème de sa mesure se pose (voir Bisias et al., 2012, pour une définition et pour une synthèse des principales mesures de risque systémique). Par définition, le risque systémique est inobservable et seuls des évènements systémiques peuvent être observés.[62] Or, dans une perspective de régulation il convient bien évidemment de mesurer et de « probabiliser » ce risque d'effondrement du système. Plus spécifiquement, la mise en place d'une régulation macroprudentielle suppose d'évaluer la contribution de chaque institution financière au risque du système, à la manière d'une externalité. Comment évaluer cette contribution d'une institution financière au risque global du système ? Comment valider une telle mesure ? Ces enjeux et les conséquences dramatiques sur l'économie mondiale de la faillite de Lehman Brothers en 2008 ont conduit à une profonde remise en cause tant des régulations prudentielles (jusqu'ici essentiellement axées sur une vision microprudentielle dans laquelle la stabilité des institutions garantit la stabilité du système dans son ensemble) que de la vision académique du risque systémique (Hansen, 2014).

Au niveau académique, le risque systémique est souvent apparenté à la notion de contagion des risques. Pour observer un évènement systémique, un élément déclencheur est requis. Selon la Banque Centrale Européenne (2009), cet élément déclencheur peut

[62]Pour être plus précis, nous devrions évoquer la notion d'incertitude systémique (au sens de Knight), dès lors que l'on suppose que les évènements systémiques peuvent être probabilisées.

venir de deux sources : un choc exogène, c'est-à-dire un évènement idiosyncratique tel que la défaillance d'un marché ou la faillite d'une institution financière, ou d'un choc endogène à l'intérieur même du système financier, c'est-à-dire un déséquilibre macroéconomique globale.[63] Ce choc se diffuse alors à travers la totalité du système financier en raison d'effets de débordement qui sont locaux et d'effets de contagion qui sont globaux. Au final, l'économie réelle est affectée, entrainant une réduction du bien-être individuel et collectif. Ainsi, la menace systémique fait référence à l'idée d'externalités négatives. La prise de risque d'une institution financière peut avoir des effets pour ses actionnaires et ses managers, mais aussi pour d'autres institutions financières (Lepetit, 2010). Cette interdépendance provient notamment des transactions financières sur le marché interbancaire (Rochet et Tirole, 1996) ou de prises de positions par les banques sur les mêmes actifs (Allen, Babus et Carletti, 2012).

L'idée globale d'une réglementation macroprudentielle consiste à internaliser ces externalités de risques financiers.[64] Ce changement de paradigme dans la réglementation prudentielle a été orchestré par une forte volonté politique internationale, comme l'illustrent les six rassemblements des chefs des gouvernements du G-20 au sujet des marchés financiers et l'économie mondiale ayant eu lieu de 2008 à 2011. Cette ligne directrice est à l'origine d'avancées significatives sur la régulation financière, se matérialisant en 2010 par le *Dodd-Frank Wall Street Reform* et le *Consumer Protection Act* aux Etats-Unis et par le troisième accord de Bâle signé par les états membres du Comité de Bâle sur la Supervision Bancaire (*Basel Committee on Banking Supervision*, BCBS).[65]

Ainsi, si la protection des consommateurs contre le risque de faillite de leur banque était au coeur des réglementations bancaires microprudentielles, la crise financière de 2008 a conduit à prendre en compte la protection de l'ensemble de l'économie et des marchés financiers au regard d'une crise systémique (Rochet, 2008). Pour limiter le risque de faillite d'une institution financière, la clé de voûte de la réglementation prudentielle Bâle II consiste à contraindre chaque banque à détenir un niveau minimum de capital, pour couvrir ses risques de marché, de contrepartie et opérationnel. Ces montants sont souvent calculés par les banques elles-mêmes via leurs modèles internes de risque. Le passage à une réglementation macroprudentielle (Bâle III par exemple) suppose donc d'identifier les institutions financières contribuant le plus au risque total du système financier : les institutions financières d'importance systémique (*Systemically Important Financial Institutions*, SIFIs). Comme ces SIFIs posent une menace majeure sur le système, elles doivent être soumises à une supervision plus étroite, à des exigences supplémentaires en capital et

[63]Voir de Bandt, Hartmann et Peydró (2012) pour une distinction claire entre un évènement systémique au sens « étroit » et au sens « large », ainsi que sa classification en un évènement systémique « fort » ou « faible ». La mise à jour de leur revue de littérature sur le risque systémique se concentre sur les effets de contagion qui sont la conséquence d'évènements systémiques forts au sens étroit du terme.

[64]Sans distinction des risques de marché, de crédit, de liquidité ou opérationnel.

[65]Les Etats-Unis sont membres de ce Comité.

à un volant de liquidité (FSB, 2011a). Ces exigences supplémentaires en capital doivent être proportionnelles à la contribution de chaque institution au risque du système.

Dans ce contexte, trois questions cruciales émergent : (*i*) comment identifier les institutions financières d'importance systémique (SIFIs), (*ii*) comment mesurer la contribution au risque systémique pour établir les surcharges en capital et (*iii*) comment révéler les interdépendances dans les prises de risque des banques, afin de prévenir la survenue d'évènements systémiques.

Identifier les institutions financières d'importance systémique

Par certains aspects, les systèmes biologiques et bancaires présentent de nombreuses similarités en tant que systèmes complexes. C'est sans doute pourquoi l'analogie de la contagion des chocs financiers à la contagion et la transmission des maladies infectieuses a été si souvent reprise dans la littérature académique (Haldane et May, 2011). Les banques en tant qu'entités interdépendantes (en raison de leurs positions croisées à l'actif et au passif et leur exposition à des facteurs de risque communs) subissent et participent aux mécanismes de contagion des chocs financiers. Néanmoins, si dans le cas des pandémies on cherche à identifier le patient zéro, dans le cas d'un système financier on cherche plutôt à identifier l'ensemble des institutions financières dont les caractéristiques (taille, interconnections, rôle spécifique sur les marchés, etc.) et l'activité engendrent la plus grande menace sur la stabilité du système financier dans son ensemble, les SIFIs ou G-SIFIs pour *Global Systemically Financial Institution.*

Comment identifier les institutions financières d'importance systémique ? Au niveau mondial, l'approche proposée par les régulateurs consiste à construire un score agrégé sur la base de différents critères reflétant les différentes facettes du caractère systémique d'une institution. Le cadre proposé par le BCBS (Financial Stability Board - International Monetary Fund - Bank for International Settlements, 2009 ; FSB, 2011b ; Financial Stability Oversight Council, 2012a) est ainsi fondé sur un score incluant cinq facteurs : la taille des banques, leur interdépendance, leur activité transfrontalière à l'échelle mondiale, l'absence de substituts directs ou d'infrastructure financière pour les services qu'elles fournissent et leur complexité. Les trois premiers facteurs sont inspirés de la recommandation du rapport de la FSB-IMF-BIS de 2009, tandis que les deux derniers ont été proposés par le BCBS pour tenir compte du fait que les SIFIs complexes et internationales sont relativement plus coûteuses et lentes à démanteler (BCBS, 2011a). Dans cette approche par les scores, la question fondamentale qui se pose au-delà du choix des facteurs constitutifs du score, est celle de leur pondération relative. Le BCBS a fait le choix d'une équipondération, chaque facteur possédant un poids total de 20% dans la construction du score. Sur le même principe, tous les indicateurs entrant dans la composition d'un facteur se voient attribuer le même poids. Ces indicateurs correspondent à des valeurs comptables ou des valeurs de marché observables (pour une liste détaillée des indicateurs voir BCBS, 2013b).

Le score individuel d'une institution financière est utilisé de deux façons. Ce dernier est tout d'abord comparé à un score limite établi par le BCBS selon leur jugement d'expert. Chaque institution financière ayant un score au-dessus de cette limite est considérée comme une G-SIFI et est soumise à une surveillance plus minutieuse. Les scores servent par ailleurs à déterminer une surcharge en capital réglementaire. Les scores des G-SIFIs sont segmentés en segments de risque homogène. Le niveau d'exigence additionnel d'absorption des pertes (*Higher Loss Absorbency*, HLA) appliqué pour couvrir leur contribution au risque systémique varie alors selon la tranche dans laquelle se trouve la G-SIFI. Cette surcharge en capital, exprimée en pourcentage des actifs pondérés en fonction des risques, va de 1% à 2,5%, ce qui correspond à une augmentation de 0,5% par tranche. Depuis 2012, la liste des G-SIFIs est publiée une fois par an.

Ce cadre réglementaire constitue aujourd'hui la référence en matière d'identification des SIFIs (Weistroffer, 2011), même si cette approche repose sur une agrégation de divers indicateurs dont certains ne sont pas publics. Toutefois, cette méthodologie soulève de nombreuses questions. Ainsi, Hurlin et Pérignon (2013) montrent que l'utilisation d'un schéma d'équipondération dans la construction du score peut conduire à surévaluer l'importance des facteurs et des indicateurs les plus volatils. Plus généralement, au-delà de la méthodologie retenue, c'est l'idée même de la publication d'une liste de SIFIs qui peut poser problème. Tout comme pour les institutions « trop grandes pour faire faillite » (*too-big-to-fail*), le fait de qualifier publiquement une institution de SIFI peut conduire à ce que cette institution soit perçue comme « trop systémique pour faire faillite » (*too-systemic-to-fail*). Dès lors, sa valorisation par les marchés peut s'apprécier indépendamment de ses efforts de gestion des risques. Autrement dit, les banques peuvent avoir intérêt à être systémique au sens de la classification du BCBS même si cela induit une surcharge de capital et une surveillance accrue de la part des régulateurs. Dans une étude empirique récente, Moenninghoeff, Ongena et Wieandt (2014) montrent que la nouvelle réglementation affecte négativement la valeur de l'institution financière nouvellement régulée, mais ils soulignent que la désignation officielle des G-SIFIs a partiellement annulé l'impact souhaité. Enfin, seuls les établissements bancaires sont jusqu'à présent pris en compte dans ce cadre réglementaire. Or, d'autres institutions financières telles que les compagnies d'assurance (van Lelyveld, Liedorp et Kampman, 2009) et les fonds d'investissement spéculatifs (*Hedge Funds*) peuvent présenter un caractère systémique dans certaines circonstances (Chan et al. 2006), l'exemple typique étant l'effondrement du fond spéculatif LTCM (*Long Term Capital Management*) en 1998.

Un autre problème de cette approche réside dans la définition du périmètre du système financier de référence (voir Zigrand, 2014, pour une définition de la notion de système dans le concept du risque systémique). Est-ce qu'un régulateur européen doit évaluer les externalités de risque engendrées par l'activité des banques européennes sur les banques asiatiques et américaines, ou au contraire se restreindre à l'analyse des impacts au niveau du système financier européen ? Plus généralement cette question s'inscrit dans le cadre de l'identification des G-SIFIs et des D-SIFIs pour *Domestically Systemically Important Financial Institutions* (D-SIFIs). L'identification des D-SIFIs est primordiale dès lors qu'un régulateur souhaite analyser l'impact d'un défaut potentiel sur un système financier ou une économie nationale ou régionale. Par exemple, en août 2014, la banque portugaise Banco Espirito Santos a été recapitalisée par une aide de l'Etat portugais de 4,4 milliards d'euros en raison de ses trop grandes expositions au risque. Cette banque n'a pourtant jamais été identifiée comme une G-SIFI bien qu'elle est obtenue de médiocres résultats aux stress tests de 2011. Afin d'identifier les sources de risque systémique à l'échelle nationale, le BCBS (2012) propose un ensemble de douze principes permettant de caractériser les D-SIFIs et d'évaluer le niveau précis de leur HLA. Malheureusement, ce cadre n'est pas encore opérationnel. C'est pourquoi l'identification des D-SIFI est aujourd'hui au centre de l'agenda de recherche tant des régulateurs que des académiques (Brämer et Gischer, 2011 ; Engle, Jondeau et Rockinger, 2014). Cette thèse contribue à cette littérature en proposant une méthode permettant de repérer les institutions financières qui pourraient potentiellement être d'importance systémique au niveau de leur pays.

La méthodologie proposée par les régulateurs n'est pas le seul moyen d'identifier les institutions financières systémiquement risquées. Les universitaires ont développé plusieurs mesures à mêmes de capturer l'importance systémique d'une institution financière. La principale difficulté pour ces derniers est qu'ils n'ont généralement pas accès à certaines données permettant de mesurer l'interdépendance au niveau des bilans des banques (Cerutti, Claessens et McGuire, 2014). C'est pourquoi les mesures de risque systémiques issues de la recherche académiques sont pour l'essentiel fondées sur des données de marché et des données de bilan publiquement accessibles.

Les mesures du risque systémique

Comme le montre l'approche réglementaire, le risque systémique ne peut pas se résumer à un seul critère. Zhou (2009) met ainsi en évidence que la taille d'une institution financière n'est pas nécessairement un bon estimateur du risque systémique. C'est sans doute cette dimension multicritère qui explique pour partie le relatif foisonnement de mesures de risque systémique dans la littérature académique. Bisias *et al.* (2012) énumèrent trente et une mesures de risque systémique provenant de la littérature économique et financière, en partant de ses fondations granulaires jusqu'à des mesures de réseaux en passant entre autres par les mesures prospectives du risque systémique. De Bandt *et al.* (2013) rassemblent également un grand nombre d'indicateurs du risque systémique, en particulier ceux mesurant la contribution individuelle des institutions financières. Ce dernier ensemble de mesures est très pertinent pour identifier les SIFIs.

Afin de juger de la contribution d'une institution financière au risque systémique, deux approches peuvent être isolées. D'un côté, les mesures se basant sur des données de marché, comme les rendements boursiers ou les données sur les contrats d'échange sur défaut ou *Credit Default Swaps* (CDS), de l'autre, les mesures utilisant les bilans comptables et les données des régulateurs (lorsqu'elles sont disponibles) telles que les expositions bilatérales des institutions financières.

Le premier sous-ensemble de mesures s'appuie sur des données de marché. Adrian et Brunnermeier (2011) étendent la VaR avec le concept de CoVaR, le préfixe Co signifiant conditionnel, contagion ou co-mouvement. La CoVaR capture la perte du système financier conditionnellement aux tensions financières d'une institution. La ΔCoVaR mesure la contribution d'une institution au risque du système. Elle est définie par la différence entre la CoVaR calculée lorsque l'institution se trouve dans une situation difficile et la CoVaR obtenue lorsque l'institution est à son état médian. Acharya *et al.* (2010) définissent la *Marginal Expected Shortfall* (MES) ainsi que la *Systemic Expected Shortfall* (SES). La MES est égale à la contribution marginale d'une firme à l'*Expected Shortfall* (ES) des rendements quotidiens du marché.[66] La SES d'une institution correspond au montant de capitaux propres se situant en dessous d'un certain niveau lorsqu'une crise systémique survient. En d'autres termes, la SES mesure la sous-capitalisation potentielle d'une institution financière lorsque le système dans son ensemble est sous-capitalisé. Brownlees et Engle (2012), Acharya, Engle et Richardson (2012) ainsi que Engle, Jondeau et Rockinger (2014) combinent la MES avec la capitalisation boursière et le montant total de dettes afin de définir une nouvelle mesure, la SRISK, qui est sans doute aujourd'hui la mesure la plus populaire. La SRISK prend en compte le levier et la taille et mesure le manque de capital attendu lorsque le système financier est en situation de stress.[67] Les auteurs interprètent la SRISK comme un manque de capital, ce qui permet de faire un lien évident avec l'objectif réglementaire d'accroissement de la stabilité financière avec une plus grande exigence en capital. Toujours en utilisant des rendements, Billio *et al.* (2012) proposent une mesure de causalité au sens de Granger permettant d'identifier les interconnexions (interprétées comme des effets de débordement) et *in fine* le risque systémique. Dans le même esprit, Diebold et Yilmaz (2014) proposent plusieurs mesures d'interconnexion obtenues en utilisant une décomposition de variance basée sur la volatilité des rendements boursiers. Les deux précédentes études identifient ainsi la topologie du système. Corradin, Manganelli et Schwaab (2011) introduisent un schéma de régressions quantiles multiva-

[66] Brownlees et Engle (2012) étendent cette mesure à un horizon temporel de six mois via la LRMES en utilisant une formule de conversion ou des simulations.

[67] La SRISK est étendue par Engle et Siriwardane (2014) en incorporant un modèle GARCH structurel qui propose un nouveau modèle de volatilité où le levier financier amplifie la volatilité des fonds propres.

riées pour jauger de la contribution d'une institution financière. Straetmans et Chaudhry (2012) appliquent une analyse statistique multivariée des valeurs extrêmes pour réaliser une comparaison transatlantique du risque systémique totale. Comme l'explique Markose *et al.* (2010), les CDS ont eu un rôle stratégique dans la crise financière et des mesures de risque systémique basées sur des données de CDS ont donc été proposées, telles que le *Systemic Risk Ratio*. Huang, Zhou et Zhu (2009) fournissent une estimation de la probabilité de défaut neutre au risque avec l'indice *Distress Insurance Premium* (DIP), tandis que Giglio (2012) calcule le risque de défaut joint des institutions financières. Au-delà de ce vaste mais non exhaustif ensemble de mesures de risque systémique basées sur des données de marché, un autre sous-ensemble de mesures mobilisent d'autres sources d'information.

Le second sous-ensemble de mesures s'appuie sur les données de bilans bancaires ainsi que celles des régulateurs. Greenwood, Landier et Thesmar (2012), en se basant sur les données publiées par l'autorité bancaire européenne (*European Banking Authority*, EBA) sur les expositions des banques à la dette souveraine européenne, distinguent la contribution d'une banque à la fragilité du secteur financier de sa propre vulnérabilité au risque systémique. Brunnermeier, Gorton et Krishnamurthy (2014) s'intéressent à la liquidité pour comprendre la crise et proposent un *Liquidity Mismatch Index* (LMI) pour évaluer l'importance systémique d'une institution financière. Comme souligné par Caballero (2010), le risque systémique est intrinsèquement lié à l'importance des interconnexions entre institutions. C'est pourquoi de nombreux travaux s'inscrivent dans une logique de modélisation du système financier en réseau. Cont, Moussa et Santos (2012) proposent ainsi le *Contagion Index* pour capturer l'importance systémique d'une institution, défini comme la perte attendue sur le système déclenchée par le défaut d'une institution à la suite d'un scénario de stress. Dans leur travail, l'importance systémique est basée sur les expositions dues à leurs contreparties. Gouriéroux, Héam et Monfort (2012) utilisent également une base de données unique et privée sur les expositions interbancaires bilatérales. Leur méthodologie permet de séparer les effets directs d'un choc (tels qu'un choc commun sur les actifs ou un choc spécifique sur une banque), des effets de contagion présents à l'intérieur du système bancaire. Demange (2011) propose le *Threat Index* reflétant l'externalité imposée par une banque faisant défaut sur le remboursement de la dette de toutes les autres banques. Cet indicateur est une mesure alternative du risque de contagion induit par une banque, la plupart du temps défini comme le nombre attendu de faillite suivant sa faillite initiale (voir Upper 2001, pour un résumé sur ce sujet). Acemoglu, Ozdaglar et Tahbaz-Salehi (2014) s'intéressent quant à eux à la topologie du réseau financier et mettent en lumière la nature robuste mais fragile des réseaux financiers mondiaux. Ce résultat signifie notamment qu'un certain type de réseau peut être très résistant à une certaine catégorie de chocs, mais fragile à un autre type de chocs.

Cette thèse se concentre sur un sous-ensemble de ces mesures individuelles du risque systémique. L'échantillon choisi pour notre étude est composé des mesures suivantes : MES, SES SRISK et ΔCoVaR. Ce choix a été guidé par leur importance dans la sphère académique et dans le débat public, leur portée auprès des régulateurs, la pertinence de leur interprétation économique et la disponibilité publique des données nécessaires à leur construction. L'objectif est donc de contribuer à la littérature visant à évaluer la validité de ces mesures de risque systémique. Brunnermeier et Oehmke (2012) proposent une définition de ce que devrait être une mesure pertinente du risque systémique, ils mettent en avant le fait que le principe d'allocation est primordial. Dans un article connexe, Brunnermeier et Cheridito (2013) suivent ces principes et suggèrent la mesure *SystRisk*. Une approche alternative est de développer une axiomatique des mesures de risque systémique (Chen, Iyengar et Moallemi, 2013), à l'image de celle proposée par Artzner *et al.* (1999) pour les mesures de risque individuelles. L'approche présentée dans ce travail est complémentaire à ces deux approches puisque nous comparons leur performance quant à l'identification des SIFIs et leur capacité à synthétiser en une seule mesure toutes les caractéristiques du risque systémique.

Mesurer le risque systémique et identifier les SIFIs requièrent une analyse en profondeur des institutions financières. Une part significative du risque systémique peut uniquement être identifiée par une analyse détaillée des activités et des stratégies communes entre les institutions financières.

Similitudes entre banques

Les institutions financières contribuant le plus au risque systémique sont soumises à un contrôle accru. Ceci signifie que les activités de marché, telles que les positions prises sur le marché et leur besoin de liquidité associé, ainsi que les expositions encourues, sont sous surveillance. Une gestion des risques saine ne constitue pas un nouveau pilier de la réglementation puisque les modèles internes développés par les banques sont déjà validés par les régulateurs à travers une approche microprudentielle. Toutefois, les superviseurs visent aujourd'hui à intégrer dans cette réglementation une dimension dite macroprudentiels, ayant pour objectif d'éviter une trop grande concentration des risques mais aussi des expositions communes et cela même lorsque prises individuellement ces institutions (FSB, 2011a).

La dépendance des risques associés aux activités des banques peut provenir de différentes sources. Tout d'abord, les banques ont parfois des incitations communes à surinvestir au même moment dans des classes d'actifs spécifiques et ce résultat peut être exacerbé par la réglementation. Par exemple, les législateurs ont demandé que les CDS soient désormais échangés via des chambres de compensation (*Central Counterparty*, CCP), ce qui pourrait radicalement augmenter la demande globale de collatéral, entraînant de potentiels effets déstabilisateurs puisque seuls quelques types d'actifs sont éligibles comme garantie par les chambres de compensation tels que la dette souveraine (Duffie, Scheicher et Vuillemey, 2014). Hirshleifer, Subrahmanyam et Titman (1994) montrent que la nature séquentielle de l'arrivée d'information a un impact significatif sur les décisions d'investissement. Les investisseurs recevant une information commune ou privée avant les autres deviennent des « preneurs de profits » de court terme et ont tendance à échanger les mêmes actifs. Acharya et Yorulmazer (2007, 2008) soutiennent que les banques ont une forte incitation à se copier, en particulier les petites banques, dans le but de maximiser leur probabilité de renflouement. Ce type de comportement augmente la vraisemblance d'une crise systémique et pose aux régulateurs le problème du « trop nombreux pour faire faillite » (*too-many-to-fail*). Farhi et Tirole (2012) affirment que les choix d'endettement privé dépendent de l'anticipation de la réaction politique sur l'inadéquation globale de la maturité. Ainsi, les banques dans leur ensemble utilisent cette asymétrie dans les échéances (en ayant recourt à trop de dettes à court terme) menant à une corrélation plus importante du risque.

En résumé, les institutions financières ont des incitations qui les poussent à prendre des positions corrélées sur des actifs potentiellement surévalués. Or, ces positions ne sont pas rendues publiques et seul le régulateur est en mesure de surveiller le degré de dépendance des risques issus de ces expositions communes.

Bien évidemment, la présence de risques corrélés est particulièrement problématique lorsque des crises financières surviennent. En effet, au moment où la volatilité de marché atteint son pic, le capital réglementaire et la demande de collatérales tendent à augmenter mécaniquement pour toutes les institutions financières. En réponse, beaucoup de banques sont obligées de liquider à la hâte leurs positions et contribuent ainsi à la crise (mécanisme de *fire sales*). Adrian et Shin (2014) illustrent empiriquement cet aspect et montrent que pour maintenir une probabilité constante de défaut, les institutions financières ajustent très fortement leurs expositions au risque lorsque l'environnement économique devient plus risqué. Brunnermeier et Pedersen (2009) proposent un modèle pour expliquer le fait que l'on observe des similitudes sur la liquidité de marché entre actifs, ce qui amplifie au final la volatilité de marché. Morris et Shin (1999) expliquent que des expositions au risque corrélées (interdépendances) entre banques conduisent à une plus grande volatilité puisque les institutions financières tendent à vendre les mêmes actifs au même moment. Ce côté caché entraîne des réactions adverses pouvant avoir des conséquences dramatiques en période de crise (Persaud, 2000). Le comportement mimétique est difficile à prouver étant donné le manque de données fiables à ce sujet. Allen, Babus et Carletti (2012) développent un modèle théorique pour analyser les interactions entre les similarités entre actifs et la durée de maturité des financements capables de générer du risque systémique. Cai, Saunders et Steffen (2014) mesurent les similitudes entre les portefeuilles de prêts syndiqués de deux banques et trouvent une corrélation positive entre cette mesure d'interdépendance entre banques et diverses mesures du risque systémique basées sur des données de marché telles que la SRISK et la CoVaR.

Il est donc primordial de prendre en compte les dépendances pouvant exister entre institutions financières. Mais force est de constater qu'il n'existe pas d'outil capable d'identifier et de synthétiser les expositions au risque au niveau d'un établissement financier pour tous ses secteurs d'activité et d'en mesurer les dépendances par rapport aux autres institutions financières. Nous nous efforcerons de répondre à cette problématique dans cette thèse en proposant une méthode innovante et simple pour mesurer les expositions au risque des banques. Cette nouvelle méthodologie peut constituer un moyen efficace de révéler les co-mouvements des expositions au risque des banques et ainsi de limiter les risques systémiques.

Le principal objectif de cette thèse est de contribuer à cette nouvelle littérature cherchant à évaluer le risque systémique en proposant trois essais sur le sujet.

Contributions

Le premier chapitre s'intéresse à l'identification des établissements bancaires ayant une importance systémique au niveau domestique (D-SIBs). Nous proposons dans ce chapitre un ajustement original de trois mesures de risque systémique, conçues dans un cadre global, afin d'évaluer leurs capacités à identifier à la fois les D-SIBs et les G-SIBs. Suivant l'esprit des accords de Bâle, ce chapitre met l'accent sur les besoins en capital qu'une banque est susceptible d'avoir en période de stress lorsque cette dernière est à la fois identifiée comme G- et D-SIB.

Le second chapitre propose une analyse théorique et empirique des principales mesures de risque systémique (MES, CoVaR et SRISK) fondées sur les données de marché (rendements quotidiens). Pour ce faire, nous considérons un modèle commun et dérivons un certain nombre de propriétés théoriques de ces mesures. Nous insistons notamment sur les conditions sous lesquelles peuvent apparaître des divergences de diagnostic suivant ces mesures pour une même institution financière. Cette analyse théorique est complétée par une analyse empirique réalisée sur un échantillon de 94 banques américaines.

Le troisième chapitre propose une mesure implicite de l'exposition des banques à plusieurs facteurs de risque. Cette approche permet d'extraire une information privée au sujet des changements de l'exposition au risque des banques à partir d'une information divulguée dans les rapports d'activité de ces banques, c'est-à-dire les VaRs désagrégées par grands facteurs de risque. Cette mesure nous permet d'étudier les dépendances existantes dans les expositions au risque de 10 grandes banques internationales.

Chapitre 1 : Where is the System ?

Le chapitre 1, intitulé « Where is the System ? », élabore une méthodologie pour identifier aussi bien les D-SIBs que les G-SIBs.[68] En s'appuyant sur le fait que les mesures standards de risque systémique basées sur des données de marché, telles que la SRISK et la ΔCoVaR, sont capables d'identifier les G-SIBs, ce chapitre propose un ajustement simple de ces mesures afin d'étudier la contribution au risque systémique d'une certaine banque au niveau domestique. L'objectif est au final de mettre en place un dispositif spécifique pour les D-SIBs comme le préconise le comité de Bâle sur la régulation bancaire (BCBS).

Dans ce contexte, même lorsque le système de référence change, ces mesures ne peuvent pas être utilisées pour distinguer une D-SIB d'une G-SIB. Ce résultat montre d'une part que la SRISK est principalement sensible au montant total de dettes de la banque, cet élément ne dépend pas de la taille du système. D'un autre côté, la ΔCoVaR est largement sensible au choix du système de référence, ce qui mène à une distinction claire entre le niveau domestique et global dans lequel l'institution agit.

Nous montrons tout d'abord que même lorsque le système financier de référence change, ces mesures ne permettent pas de distinguer une D-SIB d'une G-SIB. Ce résultat s'explique par le fait que la mesure SRISK est principalement sensible au montant total de dette de la banque. Or, cet élément ne dépend pas du choix du système financier de référence (domestique ou global). Ce problème est illustré à l'intérieur de l'eurozone où l'identification des D-SIBs est très importante. Nous proposons un indicateur basé sur la différence entre deux SRISKs calculées respectivement au niveau national et européen. Nous montrons que cet indicateur est un outil prometteur dans l'optique d'identifier les D-SIBs et d'évaluer le manque de capital potentiel qu'une banque peut avoir lorsque cette dernière est considérée à la fois comme D-SIB et G-SIB.

Chapitre 2 : A Theoretical and Empirical Comparison of Systemic Risk Measures

Le chapitre 2, intitulé « A Theoretical and Empirical Comparison of Systemic Risk Measures », délivre une analyse théorique et empirique des principales mesures de risque systémique basées sur données de marché (MES, SES, SRISK et ΔCoVaR) actuellement utilisées par les banques centrales et les agences de régulation bancaire.

Le comité de stabilité financière (*Financial Stability Board*, FSB) recommande qu'une mesure de la contribution d'une institution financière au risque systémique global doit refléter la taille, le levier, la liquidité, l'interdépendance, la complexité et la substituabilité de cette dernière. Or, les résultats de ce chapitre indiquent que ces mesures ne remplissent pas complétement cette tâche et ne reflètent qu'imparfaitement la nature multidimensionnelle du risque systémique. Cette recherche constitue la première tentative

[68] Ce chapitre est publié dans la revue *International Economics*.

de comparaison, théorique et empirique, de ces principales mesures de risque systémique. Le résultat principal de notre étude est que la plus grande part de la variabilité de ces mesures systémiques peut être capturée par de simples mesures du risque de marché (pris en isolation) ou alors par des caractéristiques de la firme.

Nous proposons tout d'abord une analyse théorique de ces mesures à partir d'un cadre unifié. Dans ce cadre stylisé, nous dérivons les expressions analytiques des mesures de risque systémique et nous mettons en évidence le lien théorique entre le risque systémique et les mesures standards de risque de marché (risque systématique, risque de queue, corrélation et beta) ainsi que des caractéristiques classiques des firmes, comme le levier et la capitalisation boursière. Plus spécifiquement, nous montrons que la MES est proportionnelle au beta, tandis que la CoVaR est fondamentalement liée à la VaR de l'institution et que la SRISK est déterminée par le beta et le quasi-levier. Nous étudions en outre les conditions sous lesquelles ces différentes mesures peuvent donner un diagnostic convergent sur le classement des institutions financières suivant leur degré de risque systémique.

Cette analyse théorique est complétée par une analyse empirique réalisée sur un échantillon de quatre-vingt-quatorze banques américaines sur la période allant de janvier 2000 à décembre 2010. Dans cette analyse empirique, nous adoptons exactement les mêmes méthodes d'estimation que celles préconisées dans les articles fondateurs. Nous montrons que ces différentes mesures empiriques de risque systémique conduisent à identifier différentes SIFIs. De plus, nous montrons qu'un modèle linéaire à un seul facteur explique entre 83% et 100% de la variabilité de ces indicateurs de risque systémique, ce résultat traduisant la dimension monocritère de ces mesures. En coupe transversale, la MES et la SRISK sont respectivement expliquées par le beta de la firme et par son montant total de dettes tandis que la ΔCoVaR, considérée dans la dimension temporelle, est principalement expliquée par la VaR.

Chapitre 3 : Implied Risk Exposures

Le chapitre 3, intitulé « Implied Risk Exposures », présente une méthode novatrice permettant de révéler les expositions au risque des grandes banques.[69] Cet essai répond ainsi au problème crucial de données auquel font face les praticiens et les chercheurs sur ces expositions (Cerutti, Claessens et McGuire, 2014). Même si les stress tests menés par l'autorité bancaire européenne (*European Banking Authority*, EBA) permettent d'observer les positions ainsi que les expositions au risque des banques, ces tests ne sont pas réalisés chaque année. Pour surmonter ce problème, ce chapitre développe une méthodologie appelée *Factor Implied Risk Exposures* (FIRE) permettant d'inférer les expositions au risque des banques à partir des publications légales de ces dernières.

[69] Cet article est à paraître dans *Review of Finance*.

L'originalité de cette technique est de montrer comment déduire des mesures de risque reportées dans les rapports d'activité, telles que la *Value-at-Risk* (VaR), une mesure implicite de leur exposition au risque par rapport au marché action, au taux d'intérêt, au taux de change et aux matières premières. Puisque ce chapitre prend en considération un large éventail de risques, il étend de fait la littérature actuelle qui se focalise exclusivement sur les expositions au risque des banques par rapport au taux d'intérêt, comme examiné par Begenau, Piazzesi et Schneider (2013) ainsi que Landier, Sraer et Thesmar (2013). Il est également montré que la structure factorielle de la volatilité du marché des capitaux, mise en évidence par Herskovic *et al.* (2014), est persistante pour nos quatre classes d'actifs, ce qui met en lumière un certain degré de similitude sur la volatilité des actifs au sein d'une même classe d'actifs. La méthode est évaluée en comparant systématiquement les expositions au risque implicites données par la méthodologie FIRE, aux déclarations faites dans les documents publics d'une grande institution financière au sujet de son actuelle exposition au risque. Les biais, sur cette mesure implicite des expositions, qui pourraient être provoqués par un risque de modèle et un risque d'estimation sont également étudiés par simulations.

L'application empirique sur dix grandes banques américaines et européennes montre que les expositions au risque sont négativement corrélées avec la volatilité de marché et que les changements de ces expositions sont positivement corrélés entre banques, ce qui est consistant avec le fait que les banques présentent des similarités dans leurs transactions financières. Le premier résultat suggère que les banques gèrent activement leurs expositions au risque en fonction des conditions de marché. Ce phénomène peut être vu comme une tentative de réduction de l'effet procyclique dû à une hausse de la volatilité sur le capital réglementaire des banques. Le second résultat indique que les banques rééquilibrent leurs portefeuilles d'une manière corrélée. Toutefois, un groupe de grandes banques ayant une exposition commune croissante à une certaine classe d'actifs est une source d'interconnexion entre institutions financières, ce qui augmente le risque systémique. Cette préoccupation est particulièrement pertinente pour les régulateurs bancaires puisqu'ils cherchent à contrôler cette interdépendance.

Sylvain BENOIT

Trois essais sur le risque systémique

Résumé :
Le risque systémique a joué un rôle clé dans la propagation de la dernière crise financière mondiale. Un grand nombre de mesures de ce risque ont été développées pour évaluer la contribution d'une institution financière au risque de l'ensemble du système. Toutefois, de nombreuses questions concernant les capacités de ces mesures à identifier les institutions financières d'importance systémique (SIFIs) ont été soulevées puisque le risque systémique possède de multiples facettes et certaines d'entre elles sont difficiles identifier, telles que les similitudes entre institutions financières.
L'objectif général de cette thèse en finance est donc (*i*) de proposer une solution empirique pour identifier les SIFIs au niveau nationale, (*ii*) de comparer théoriquement et empiriquement différentes mesures du risque systémique et (*iii*) de mesurer les changements d'expositions au risque des banques.
Tout d'abord, le chapitre 1 propose un ajustement de trois mesures de risque systémique basées sur des données de marchés et conçues dans un cadre international, afin d'identifier les SIFIs au niveau national. Ensuite, le chapitre 2 introduit un modèle commun dans lequel plusieurs mesures du risque systémique sont exprimées et comparées. Il y est théoriquement établi que ces mesures de risque systémique peuvent être exprimées en fonction de mesures traditionnelles de risque. L'application empirique confirme ces résultats et montre que ces mesures ne sont pas capables de saisir la nature multidimensionnelle du risque systémique. Enfin, le chapitre 3 présente la méthodologie appelée *Factor Implied Risk Exposures* (FIRE) permettant de décomposer une variation de la mesure de risque d'une banque en deux éléments, le premier représentant la volatilité de marché et le second correspondant à l'exposition au risque de la banque. Ce chapitre illustre empiriquement que les changements d'expositions au risque sont corrélés positivement entre les banques, ce qui est cohérent avec le fait que les banques présentent des similitudes dans leurs prises de positions sur le marché.

Mots clés : Risque systémique, Régulation bancaire, Institutions financières d'importance systémique, MES, SRISK, CoVaR, Divulgation des risques, VaR, Capital Réglementaire.

Three Essays on Systemic Risk

Abstract:
Systemic risk has played a key role in the propagation of the last global financial crisis. A large number of systemic risk measures have been developed to quantify the contribution of a financial institution to the system-wide risk. However, numerous questions about their abilities to identify Systemically Important Financial Institutions (SIFIs) have been raised since systemic risk has multiple facets, and some of them are difficult to gauge, such as the commonalities across financial institutions.
The main goal of this dissertation in finance is thus (*i*) to propose an empirical solution to identify domestic SIFIs, (*ii*) to compare theoretically and empirically different systemic risk measures, and (*iii*) to measure changes in banks' risk exposures.
First, chapter 1 offers an adjustment of three market-based systemic risk measures, designed in a global framework, to identify domestic SIFIs. Second, chapter 2 introduces a common framework in which several systemic risk measures are expressed and compared. It is theoretically shown that those systemic risk measures can be expressed as function of traditional risk measures. The empirical application confirms these findings and shows that these measures fall short in capturing the multifaceted nature of systemic risk. Third, chapter 3 proposes the Factor Implied Risk Exposures (FIRE) methodology which breaks down a change in risk disclosure into a market volatility component and a bank-specific risk exposure component. This chapter empirically illustrates that changes in risk exposures are positively correlated across banks, which is consistent with banks exhibiting commonality in trading.

Keywords: Systemic Risk, Banking Regulation, Systemically Important Financial Institutions, MES, SRISK, CoVaR, Risk Disclosure, VaR, Regulatory Capital.

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